The Attractor Method
and its application in running, bicycling and Nordic skiing

Doctoral thesis for obtaining the
academic degree Doctor of
Social Sciences (Dr. rer. soc)

submitted by
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Konstanz

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Konstanz, 2021
Date of the oral examination: 29th March 2021

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In my opinion, the two most important things in the life of a scientist are insatiable curiosity and a well-equipped laboratory. I am lucky that mine has always been outdoors with my most valuable tools being my body, running shoes and my bicycle.
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Acknowledgments

First of all, I would like to thank all persons who were in any way involved in the completion of this dissertation.

I would like to express a sincere thank you to:

- my PhD mentor Prof. Dr. Manfred Vieten, who has always supported and challenged me. Whenever any kind of support was necessary, his door stood open. I highly appreciate that he has always respected my unusual way of working and my passion for endurance sports. His attitude towards subject-specific and social topics and in particular his great scientific knowledge will have a long-lasting and positive impact on my career.

- my supervisor at Northern Michigan University, Prof. Dr. Randall Jensen, for his caring and educational guidance throughout our entire collaboration and especially during my stays in Marquette (USA).

- the Stiftung der Deutschen Wirtschaft (sdw) which not only provided me with a scholarship for three years, but also gave me the great opportunity to look beyond the boundaries of sports science, both academically and socio-culturally.

- the sports science departments in Saarbrücken, Konstanz and at the Northern Michigan University for teaching me the basic knowledge and helping me to evolve as a sports scientist.

- Valentin Barth and Stephanie Moore, two excellent researchers in their respective field who always supported me with their knowledge and their qualified feedback.

- the sport of triathlon, which taught me to handle the roller-coaster ride of frustration, joy, insecurities, achieved milestones and inner struggles.

- my family, which in its own way always reminds me of my origins and has always stood behind me without any moment of hesitation.

- my beloved partner Carmen, for your love and the shared passion for sports. Especially for your understanding, patience and endless assistance during my PhD.

I dedicate this work to my parents and grandparents
Summary

Physical activity plays a major role in daily life of a human being. This is especially true when considering bipedal locomotion but can also encompass swimming or riding a bicycle for example. The analysis of human motion becomes particularly interesting when it has to be learned (during growth), when it is limited (in cases of disease and rehabilitation), or for the purpose of improving physical performance (as for sport). In this cumulative dissertation a modern approach, the so-called attractor method, is applied to kinematically differentiate human cyclic motion, especially running. Two theoretical papers have been published in international journals. Two additional works provide insight into the fields of application of the method and its significance for sports practice.

The first theoretical work describes the kinematic components of cyclic human running motion using the attractor method. The model presented can be described by six superimposed components: first, the individual attractor, i.e., the running movement itself, and morphing, which represents continuous deviations from it during the course of the run. In addition, the transient effect, which explains fluctuations in running behavior that occur especially in the first minutes after the onset of a session. In addition, there are less strong factors such as short-term fluctuations, a control mechanism that directs the movement back to the attractor should it deviate too much from it, and finally technical noise, which is derived from the measurement technology. The corresponding analyses and validation were performed with both, measured and simulated data.

In a second, continued work concerning the above-mentioned factors, the transient effect was investigated in more details. This aspect is particularly interesting from a practical point of view, since many athletes report an arrhythmic feeling at the beginning of a running session. However, this sensation should diminish after a few minutes, once the athletes have found their rhythm. With this study it was possible to objectively quantify exactly this initial feeling. In addition, the methodology also made it possible to estimate the duration of this transient phase and to check whether it is related to athletic performance.
and training experience. These findings provide novel information for a proper estimation of human running and thus a possible tool to steer athletic running performance.

Two further application studies support the theoretical works described above in terms of its practical relevance. It is known that familiar people can often be recognized by their posture or gait pattern even from a distance. With the help of the attractor method, we created a gaitprint for each recorded runner in the first of the two application-oriented papers. The gaitprint refers to an individual attractor that is so typical and inherent that the respective person can be identified with a very high probability solely on the basis of it. Despite the strong individuality of the gaitprints, it is still possible to create a global attractor for the running movement itself. Another practical project was conducted at Northern Michigan University in Marquette (MI, USA) with the local cross-country skiing college team. The skating technique of 16 athletes was examined and the attractor method was used to identify the respective techniques, the so-called V1 or V2 style. In addition, individual technique assessments were carried out for case studies, which made it possible to obtain a differentiated impression of leg, arm and trunk movements. Overall, the findings of both studies open up new possibilities to analyze movements of cyclic sports in a cost- and effort-efficient way and to upgrade identification algorithms to the detection of movements.
Summary (in German language)

Bewegung spielt für den Alltag aller Menschen eine übergeordnete Rolle. Dies gilt besonders, wenn es darum geht, uns fortzubewegen. Meistens zu Fuß, aber auch schwimmend oder beispielsweise auf dem Fahrrad. Die Analyse dieser menschlichen Bewegung wird vor allem dann interessant, wenn sie neu erlernt werden muss (Wachstum), nur noch eingeschränkt möglich ist (Krankheit und Rehabilitation) oder zwecks Verbesserung der körperlichen Leistungsfähigkeit (Sport). In dieser kumulativen Dissertation wird ein moderner Ansatz, die sogenannte Attraktor Methode, angewandt, um menschliche zyklische Bewegungen, besonders das Laufen, kinematisch zu beschreiben. Zunächst wurden hierzu zwei theoretische Arbeiten in internationalen Journals publiziert. Zwei weitere geben einen tiefergehenden Einblick in die Anwendungsfelder der Methode und deren Bedeutung für die sportlichen Praxis.


In einer weiterführenden, zweiten Arbeit wurde einer der oben aufgeführten Faktoren, der Transienten Effekt, tiefergehend untersucht. Dieser ist im Besonderen auch aus praktischer Sicht interessant, da viele Sportlerinnen und Sportler zu Beginn einer Laufsession von einem unrunden Laufgefühl berichten. Dieses solle sich hingegen nach wenigen Minuten wieder bessern, wenn man

Abbreviations

°/s ...................................................................... Unit of angular (rotational) speed
3D ...................................................................... Three dimensional
absolute D ............................................................ Motion variability in a single attractor
AFF ................................................................. *Ausschuss für Forschungsfragen* = Research committee
BC ..................................................................... Before Christ
BORG CR-10 scale ........................................... Scale to assess the subjective exertion between 1 - 10
CoH (t) .................................................................. Collection of harmonics
CoHmod (t) .......................................................... Collection of harmonics (modified method)
csv ....................................................................... Microsoft Excel data format
\(e^{-1}\) ................................................................. negative exponentially
e-learning ........................................................... electronic learning
EMG ...................................................................... electro-myography
Eq ....................................................................... Equation
e-sports ........................................................... electronic sports
et al. ................................................................. lat. et alii, et aliae, et alia = and co-worker
etc. ................................................................. lat. et cetera = and so on
FFT ................................................................. Fast Fourier Transform, also method to test transient effect
FFTmod ............................................................ Fast Fourier Transform, modified version to test transient effect
Fig (s) ................................................................. Figure (s)
FKS ...................................................................... Fatigue Index Kliniken Schmieder
g ....................................................................... gram / gravitation
G ......................................................................... gravitation
Gauss .................................................................... magnetic flux density
h .......................................................................... hour(s)
h/week ............................................................. Training time in hours per week
Hz .......................................................................... Hertz
i.e. ...................................................................... Lat. id est = that is to say
ICC ...................................................................... Intraclass coefficient
IRONMAN ........................................................... International triathlon series
IRun ................................................................... Running without prior load
kg ........................................................................ kilogram
km ........................................................................ kilometer
km/h ..................................................................... kilometer per hour
LT .......................................................................... lactate step test
m .......................................................................... meter(s)
m/s^2 .................................................................... Unit of acceleration
MATLAB .......................................................... 'Matrix Laboratory', software by MathWorks
MEMS .................................................................. Micro-electrical-mechanical-system
MI ........................................................................ Michigan
min ....................................................................... minute(s)
mm ........................................................................ milimeter
n ................................................................. number of data points / subjects / cases
N .......................................................................... number of subjects
n.d. ................................................................. not dated
p ................................................................. p-value expressing statistical probability
p. .......................................................................... Page
The mathematical equations presented in the various studies are not listed separately in this catalog. They are always explained in direct context below the formula.
1 General introduction

The analysis of human movement, in particular locomotion like walking and running, has been a fundamental research topic for many years (Al-Zahrani & Bakheit, 2008; Baker, 2007; Colyer, Evans, Cosker, & Salo, 2018). This has led to the development of versatile research approaches, scientific works, and practical applications that have great potential to improve many aspects of life. This is especially relevant in the growing health and fitness sector, where movement tracking has become increasingly popular (Allen, Ambikairajah, Lovell, & Celler, 2006; Xie et al., 2018). Further, rehabilitation settings utilize many of these approaches in the gait and posture analysis of patients (Sweeting & Mock, 2007). In addition, these analyses play an increasingly important role in occupational medicine to reduce cases of WMSDs, Work-Related Musculoskeletal Disorders, (Cerqueira, Ferreira da Silva, & Santos, 2019; Nath, Akhavian, & Behzadan, 2017; Tee et al., 2017) and especially in leisure and professional sports where movement efficiency is decisive to performance (Conley & Krahenbuhl, 1980; Ohgi, Ichikawa, & Miyaji, 2002).

Lately, technical developments like wearable sensors have contributed significantly to further scientific progress and achievements. For example, so called micro-electro-mechanical system (MEMS) sensors (Caldas, Mundt, Potthast, Buarque de Lima Neto, & Markert, 2017), which are even built into modern smartphones, can register movements in three dimensions with high sensitivity and present them in a very time- and cost-efficient manner. This enables the collection of a high quantity of data per time unit and a correspondingly accurate representation of the movement sequences. These data can be made accessible for movement analysis by applying modern computer-based analysis methods, such as the ‘attractor method’ which was introduced by Vieten, Sehle and Jensen (2013, p. 3). Their method was developed to analyze human movements and encourage the identification of changes in movement patterns on the group and individual level. To apply their method and produce an attractor (essentially a mean value of the recorded movement sequence), it is necessary to capture motion data from sports with cyclic movements, such as running, cycling, or swimming. These data are used to describe the movements kinematically, i.e. the consideration of the laws of
motion without the inclusion of internal or external forces. Thus kinematics is dealing ‘with the details of the movement itself’ (Winter, 2005, p. 45) These repetitive movements, like running, can be described by a limit-cycle (Strogatz, 2015, pp. 198–201; Vieten et al., 2013, p. 2). Based on these considerations, the comparison of attractors of different sequences allows the identification of changes in movement characteristics or variability. In this respect, the attractor method was initially applied to therapeutics (Broscheid, Dettmers, & Vieten, 2018; Byrnes et al., 2018; Sehle, Vieten, Mündermann, & Dettmers, 2014; Sehle, Vieten, Sailer, Mündermann, & Dettmers, 2014) before it was further developed to recreational and competitive sport performance within the context of the current doctoral thesis.

The purpose of this dissertation was to improve and utilize the attractor method to achieve deeper understandings of cyclic human motion. Moreover, in terms of athletic performance, this thesis aimed to get further insights into the qualitative and quantitative aspects of locomotion. The foundation for the use of the attractor method exists in a fundamental publication (Vieten & Weich, 2020), where theoretical and mathematical considerations of the individual kinematic contributions of human cyclic movements are described. One of the kinematic components that needed consideration for this fundamental description, termed ‘transient effect’ (Weich, Vieten, & Jensen, 2020), was investigated in more detail. A transient kinematic pattern was identified at the onset of many running sessions, which often subsided after a few minutes once the athlete had found his or her rhythm. This period often coincided with the subjective sensation of athletes who describe this phase to be unsteady and arrhythmic. To demonstrate its practical usability, the attractor method was applied in the context of a gait recognition study, which resulted in a high identification rate of persons based only on their individual running motion, which was designated as the ‘gaitprint’ (Weich & Vieten, 2020). Furthermore, in a project conducted at Northern Michigan University (MI, USA), the theoretical considerations were applied to cross-country skiing. Thus, the attractor method was used to visualize subtle differences in cross-country skiing skating techniques (Weich, Moore, Fjeldheim, & Jensen, 2020). The essential works of this doctoral thesis suggest that the attractor method, in combination with the data from MEMS sensors, is a highly sensitive and cost-efficient tool to increase knowledge of human locomotion.
Importantly, it can be applied to many sports and movement science queries, which makes it a useful tool for practical users like coaches, athletes, and sports scientists. Consequently, the current thesis advances the theoretical knowledge of human cyclic motion but also demonstrates the potential to transfer this information into practice.

1.1 Human locomotion kinematics and assessment

Human movement quality has been a matter of interest for many years (Al-Zahrani & Bakheit, 2008; Baker, 2007), ultimately warranting the emergence of the biomechanics and movement science research branches in recent decades. These research branches deal with motion sequences of biological systems under consideration of mechanical laws. One major element of biomechanics is the consideration of the kinematics, i.e. the spatio-temporal description of a movement, without taking into account the internal and external forces (Güllich & Krüger, 2013, p. 127; Winter, 2005, p. 45). The kinematics are not only defined by positions in space, rather also their development over time (i.e. velocity and acceleration). Kinematics, in the context of human motion, had already been the focus of early approaches. Aristotle (384-322 BC) already made note of gait information that was perceived with his naked eye (Baker, 2007, p. 331). However, the first serious efforts to understand the human gait in detail, which can only succeed experimentally, are attributed to Giovanni Borelli in the 17th century. He carried out some basic experiments and gained insights into the various phases of the gait cycle and muscle activity during walking (Al-Zahrani & Bakheit, 2008; Baker, 2007; Borelli & Maquet, 2014). In the 200 years following Borelli, further novel observations were reported (for an overview, see Baker, 2007, p. 332), which ultimately served as the basis for the first extensive experiments that resulted in the development of the pendulum theory of human gait (Weber & Weber, 1837). This theory described the human gait as a passive forward swing of the legs, which is similar to the movement of a pendulum solely ruled by gravity (Kietz, 1966, pp. 11–12).

The works of Weber and Weber provided the basis for the next steps in kinematic analysis in the late 19th and early 20th century. Chronophotography, an analysis method that shows an entire movement series in one concise picture, is
particularly associated with the works of Marey (Braun & Marey, 1994), a French physiologist, and Muybridge (1979), an English photographer. This method allowed a step-by-step inspection of motion sequences. Moreover, the works of Christian Wilhelm Braune and Otto Fischer, who published ideas to determine the body’s center of gravity (Braune & Fischer, 1985 & 1987).

Further progress of movement analysis has always grown in conjunction with the development of contemporary technologies. Since the middle of the 20th century, the focus has been on sensor- and camera-based systems. The method for both systems has been gradually automatized in order to work more time-efficiently. Although techniques using accelerometers or gyroscopes (Mayagoitia, Nene, & Veltink, 2002) became available in the 1950s to 1970s (Al-Zahrani & Bakheit, 2008, p. 106), it was mainly indirect, vision-based systems with active or passive markers for anatomical landmarks that were preferred for sport scientific measurements (Colyer et al., 2018). The great advantage of the latter systems is that person being analyzed can move very naturally, as there is no need to attach large sensors or cable connections. However, these immensely developed laboratories are very costly and are thus not universally available. Moreover, for studies on a treadmill, the data would be hard to interpret if a person would stay at different treadmill positions during several test sessions. The latter requires a very intensive calibration before each data acquisition and a generally very standardized laboratory setting.

On the other side, when wearing wireless MEMS-sensors, runners are able to perform more naturally and can be equipped in a frictionless way. Thus, a sensor-based data collection was preferred when carrying out the studies that contribute to this dissertation. Further, it is also known that acceleration data can be derived mathematically by the coordinate data collected from a marker based digitizing system, however during integration information gets always lost due to a smoothing process. Today’s sensors are usually built as a MEMS; they are small, light and above all barely perceptible for the subjects. MEMS do function as a combination of an accelerometer, gyroscope, and magnetometer and collect data with a high sensitivity. Hence, with their modern construction they boast low acquisition costs and flexible application in sports scientific or rehabilitative contexts (Espinosa, Lee, & James, 2015; Gouwanda & Senanayake, 2008; LEOMO Inc., 2017; Yang & Hsu, 2010).
The fact that kinematic analysis has been studied intensively for so long that acquisition systems have been developed and refined enabling precise analysis of human motion, testifies the utmost importance of this topic for sports and human sciences in general. The initial motivation to understand the development of human locomotion as well as the difference to other species was, apart from evolutionary reasons, also medical. The advancements which were learned from medical science, such as the understanding of the human musculoskeletal system, made it possible to develop high-tech aids and devices for rehabilitation or injury prevention. On the basic knowledge of the latter, motion assessments expanded further to the field of high-performance sports. One of the main pillars of success in many sports disciplines is to execute the movement as efficiently, i.e. energy-saving, as possible. When considering a world-class marathon performance, it becomes clear that although it depends on metabolic factors, like maximum oxygen consumption (VO$_{2\text{max}}$), the economy of the running movement is the decisive criterion for success (Saunders, Pyne, Telford, & Hawley, 2004). In order to improve the latter even further, athletes are turning to running shoes with carbon soles which allowed a marathon time under two hours for the first time (Keh, 2019). Product developments and also the evaluation of foot mechanics in general have benefited enormously from modern sensor technologies (Muniz-Pardos et al., 2018; Wagner, 2018). Thus, the analysis of human bipedal locomotion is one of the most relevant assignments for sports science with regard to potential further development of athletic performance.

1.2 The attractor method – an approach to analyze human cyclic motion

Research questions arise from issues, such as those mentioned above, which must be answered with scientific methods. An important approach emerged regarding the interpretation of individual gait data through the introduction of the attractor method by Vieten and colleagues (2013). The approach was further refined in a therapeutic context by Aida Sehle (2015). Generally, the attractor method should allow the analysis of human movements, especially of cyclic motions like walking, running, cycling, or skiing, which can all be described with a movement attractor. Simply put, an attractor embodies an equilibrium region in
phase space representing the complete dynamical system (Newell, van Emmerik, Lee, & Sprague, 1993). A phase space, in the physical sense, is a mathematical construct that describes all possible states of a system based on one or more variables. Considering the variability of these states over time, the dynamical development of a system is expressed (Kellert, 1993, p. 2). An attractor represents a path in phase space to which the trajectories of a system converge, regardless of their initial state, even when affected by any kind of perturbation (Newell et al., 1993; Strogatz, 2015, p. 198). This ‘magnetic attraction’ (Briggs & Peat, 1995, p. 49) to the entire system characterizes the attractor as an equilibrium region. Attractor types can be distinguished very clearly by their complexity. The simplest version would be a fixed-point attractor, a system where all variables converge to a single point, like a marble in a bowl, which eventually must come to a stop at the lowest point (p. 49). However, human cyclic motion is much more complicated. Instead of converging towards a fixed point, it rather finds a multi-dimensional path, a kind of closed loop known as a ‘limit-cycle attractor’ (Briggs & Peat, 1995, p. 50; Newell et al., 1993, p. 226; Strogatz, 2015; Vieten et al., 2013, p. 2). In most of the biomechanical studies until the 90s and early 2000s, research groups used conventional parameters like for example stride-frequency or -length information (Gohlitz, Große, & Witt, 1994, p. 131), ground contact time (Sterzing, Brauner, & Milani, 2009) or lower-limb range of motion (Connick & Li, 2015), which represented only a part of the content about the gait movement itself. This can lead to a meaningful loss of essential information. Initial ideas to compensate these limitations of the traditional approaches was investigated by scientists using chaos theory-based approaches (Alligood, Sauer, & Yorke, 2000). The latter are based upon the belief that the world is fully deterministic and can therefore be solved with differential equations, which are not specified for human locomotion.

One approach analyzing the dynamics of human gait using the latter procedure, was provided by Perc (2005). The author introduced the ‘embedding theorem, which enables the reconstruction of the phase space from a single observed variable’ (p. 526). This could be linked to a single acceleration axis measured at the foot. Based on Takens’ work on the embedding theorem (Takens, 1981), Perc (2005) tried to approximate to a better understanding of human gait by various nonlinear time series analyses of a short data set recorded from human
gait (pp. 525). Eventually the author concluded, that one must consider that such motion data possess a deterministic signature in the short term, whereas viewed on a long-time scale, they are highly affected by stochastic environmental influences (p. 533). Further, by calculating the maximal Lyapunov exponent $\lambda$ (Alligood et al., 2000, p. 106; Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Lyapunov, 1992; Perc, 2005, pp. 531–532; Rosenstein, Collins, & De Luca, 1993), it can be checked if originally nearby trajectories within a phase space diverge over time. If the exponent $\lambda$ is not significantly greater than zero, and thus there is no exponential divergence of neighboring trajectories, deterministic properties can be attributed to them. From this you can also make a statement about the stability of the motion. Although the latter would imply that human motion is deterministic and thus calculable by differential equations, this is not descriptive of human nature. Instead, when working with data derived from human movements like running, these are affected by stochastic elements (Goldberger, Peng, & Lipsitz, 2002; Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Ibe, 2013) leading to fluctuations around a stable limit cycle attractor which can be calculated. Even if these former approaches might have produced meaningful results on group level, they seem to lack options for individualized comparisons. However, the attractor method is capable of this with precision without the loss of essential information; the marginal risk of having 'the real attractor outside [a 5-sigma error bar range] is two in a million!' (Vieten & Jensen, 2015, p. 100).

Upon this basis, studies using the attractor method were first conducted in settings with healthy subjects (Vieten et al., 2013) and later with MS (Sehle, Vieten, Sailer, et al., 2014) as well as stroke patients (Sehle, Vieten, Mündermann, et al., 2014). The data analyzed were based on acceleration signals, which were easily collected with a MEMS sensor attached to each foot. Statfree, a software solution freely accessible online (VietenDynamics, University of Konstanz, Germany), processed these data to depict an average representation of the captured walking sequence (attractor) surrounded by various distributions of movement deviations. Based on the latter, the authors aimed to get objective numbers to quantify the differences in human gait data by calculating three main parameter: First, $\delta M$, a reference value describing, the velocity normalized difference between two attractors (Vieten et al., 2013, p. 3).
For instance, this would be the difference between attractors of two walking or running trials. $\delta M$ provides information about changes concerning the individual running pattern. Secondly, the absolute $D$, which characterizes the amount of movement deviation around a single attractor, for example the average deviation of all the cycles within a one minute running interval. Accordingly, $\delta D$ equates to the difference between the variabilities of two separate attractors’ fluctuations. Thus, the latter can provide information about the movement precision. This approach was further developed by Sehle, Vieten, Sailer, Mündermann et al. (2014) with the purpose of combining the multiplication of $\delta M$ and $\delta D$ to $\delta F$, which was subsequently referred to as ‘Fatigue index Kliniken Schmieder (FKS)’. With this development, quantification of motor fatigue could thus be used as a clinical diagnostic tool. Until that time, procedures had only allowed for group results, but the aforementioned developments were especially relevant for clinical assessments where the quantification of individual alternations indispensable.

In the following years, the initial research by Prof. Vieten and the approaches of Sehle and colleagues were continued with regard to clinical applications by Kim-Charline Broscheid. In her master thesis (Broscheid, 2016) she focused on the question how the results of a conventional clinical walking test (10 m test and 6 minute test) can be compared to an analysis using the attractor method. In short, Broscheid (2016) was able to demonstrate that patients’ walking performance changed positively during rehabilitation with the conventional analyses (i.e. 10 m/ 6-minute walking test and 12 Item MS walking scale questionnaire). This was consistent with the results of the attractor method, which revealed much more detailed results. The latter included the observation of right-left symmetry of leg movement and the variability of movement (absolute $D$ and $\delta D$). In her most recent work Broscheid and colleagues (2018) investigated changes in walking patterns, measured by comparing the attractors ($\delta M$) throughout the course of a rehabilitation training. The most significant outcome using attractor method was that the attractors of a person in the course of rehabilitation were very robust and almost invariable. These findings, alongside with a publication by Byrnes et

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1 $\delta M$ and $\delta D$ are abstract expressions and the dimensions are not of particular importance (...) [nevertheless] $\delta M$ is given in $s^{-1}$ while $\delta D$ and absolute $D$ has the dimension $m/s^{2}$ (Vieten et al., 2013, p. 4). For the mathematical derivation of all mentioned output values see (Vieten et al., 2013).
al. (2018), who also examined potential changes in attractors over time, provided the idea that people have a highly individual style of locomotion by which they might be identified. This phenomenon, later termed as ‘gaitprint’ (Weich & Vieten, 2020), is one of the central sections of this dissertation.

1.3 Working steps and hypotheses

The attractor method’s successful use in therapeutic applications opened up the possibility of implementing the method for the analysis healthy subjects in the context of cyclic sports (i.e. running, cycling, or swimming). The first use of the attractor method in cyclic sports was a comparative study between an isolated 5000 m run versus a 5000 m run after previous cycling. This study was conducted as a collaborative project with the research group of Prof. Dr. Randall Jensen at the Northern Michigan University (Marquette, MI, USA) and involved 36 very well-trained endurance athletes. The overall purpose of this study was to quantify relevant differences in athletes’ running patterns ($\delta M$) and in movement precision (absolute $D$ & $\delta D$) comparing a 5000 m race-pace run after a preceding 30-minute cycling session (TRun) to an isolated running condition over the same distance (IRun). A special focus lay on the crucial time span starting immediately after the transition from cycling to running, lasting approximately five to seven minutes (onset). The result, which was later published in the Journal Sports Biomechanics (Weich, Jensen, & Vieten, 2019), showed strong variations in the variables describing differences in movement patterns ($\delta M$) and precision ($\delta D$), in the first about five minutes in contrast to the rest of the running session, regardless of whether the run was performed isolated or after prior cycling. This inspired the hypothesis that an athlete may need to familiarize to their movement at the beginning of a running session, or possibly more generally during cyclic movements. This process of finding rhythmicity was subsequently referred to as the 'transient effect' (Weich, Vieten, et al., 2020), which will also be central theme of the current dissertation.

In summary, the current dissertation concentrates on the further development of the attractor method in athletic contexts. Specifically, one focus was on the kinematic decoding of human cyclic motion (see study 1 & 2), and the second was to test its application in two different contexts (see studies 3 & 4). These
works aimed to extend the understanding of cyclic human movements on a general level and further to enable individual performance diagnostics.

The first study (Vieten & Weich, 2020) aimed to broaden the scope of the previous findings of clinical applications and to provide the necessary basis for future work concerning the kinematics of cyclic human motion. Within this article, a mathematical model that quantitatively describes the kinematic components of a cyclic human motion, like running, was presented. This model was subsequently tested using acceleration data from treadmill running and cycling on a bicycle ergometer. The model analysis was done methodically to verify the different kinematic components. A validation database consisted of data from athletes running and cycling (n = 10) for one hour at a constant speed and cadence/power across five days (separated by at least 48 hours). In order to validate the measured raw data, the calculated attractors were transformed back into raw data using simulation algorithms. This allowed a comparison between actual and predicted raw data. In summary, the first paper discusses the following main topics:

| Table 1: Research questions study 1 |

<table>
<thead>
<tr>
<th>Objective 1.1:</th>
<th>Can the kinematic components of a cyclic human motion be described by a mathematical model?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothesis 1.1:</td>
<td>The kinematic components of human cyclic motion can be described by a mathematical model.</td>
</tr>
<tr>
<td>Objective 1.2:</td>
<td>Can the mathematical model be applied to measured running and cycling data, in a way that resulting constants and the attractor can be simulated to generate analogous raw data?</td>
</tr>
<tr>
<td>Hypothesis 1.2:</td>
<td>Raw data can be reconstructed by a simulation based on the constants and attractor retrieved from the application of the mathematical model on the measured data.</td>
</tr>
</tbody>
</table>
**Objective 1.3:**
Do similarity analyses between the data of one person and the other participants yield the same result structure for measured and simulated data sets?

**Hypothesis 1.3:**
Both data sources, measured and simulated run/bike data, lead to the same result structure after conducting similarity analyses.

It has already been shown in a previous work (Weich et al., 2019) and was further supported in study 1 that the transient effect had a significant impact on the initial phase of a cyclic motion. Thus, the second paper (Weich, Vieten, et al., 2020) was focused explicitly on the quantification of this phenomenon. It was also of interest if the duration of such a transition phase and whether surveyed anthropometric and training-related data could be linked to the transient effect.

Thirty active and experienced runners ran for two 60-minute bouts on the treadmill performing at a moderate speed. The participants were equipped with MEMS sensors attached to the ankles. In order to realize the detection of the transient effect methodically, the collected raw data first had to be prepared using the attractor method resulting in attractors which could be processed by a Fast Fourier Transformation (FFT). This allowed the isolation of the harmonics of the data set, because it was hypothesized that they are specifically influenced by the transient effect. Further components of cyclic human motion, such as noise, morphing, and short-term fluctuations (etc.) could be distinguished using this approach. It was hypothesized that the nature of the transient effect depends on athletic experience and/or level (study1; Vieten & Weich, 2020); therefore a short questionnaire was included to gather this information. For practical purposes, the following questions had the highest importance:
**Table 2: Research questions study 2**

<table>
<thead>
<tr>
<th><strong>Objective 2.1:</strong></th>
<th>Can the transient effect for athletes with moderate running speed be quantified objectively using attractor data derived from the attractor method?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Hypothesis 2.1:</strong></td>
<td>The transient effect can be quantified objectively for athletes running with at a moderate speed based on attractor data.</td>
</tr>
<tr>
<td><strong>Objective 2.2:</strong></td>
<td>Can the attractor method be employed to extricate the magnitude, and thus the duration, of the transient effect from raw data?</td>
</tr>
<tr>
<td><strong>Hypothesis 2.2:</strong></td>
<td>The duration (time in minutes) of the transient effect can be determined based on attractor data computed by the attractor method procedure.</td>
</tr>
<tr>
<td><strong>Objective 2.3:</strong></td>
<td>Does an athlete’s training level, athletic experience, or anthropometric preconditions have an influence on the duration of the transient effect?</td>
</tr>
<tr>
<td><strong>Hypothesis 2.3:</strong></td>
<td>Training level, athletic experience, or anthropometric preconditions have an influence on the extent of the transient effect.</td>
</tr>
</tbody>
</table>

As described in the previous chapter, several works suggested that the individual attractor seems to be invariant in so far that it could be referred to as a gaitprint similar to a fingerprint (Broscheid et al., 2018; Byrnes et al., 2018). In extension of this analogy, it could be hypothesized, that individuals could possibly be identified solely by their locomotion. The purpose of the third study was to test this assumption using the theoretical knowledge and the experience gained from the first two works by applying the attractor method analysis to the running patterns of 30 participants. Acceleration data were collected on three different days at a constant running speed over 20 minutes. They were gathered from the lower extremities (via a MEMS sensor at each ankle) so that the setup represented the running kinematics. Using a comparison algorithm, each
individual running session of a participant was subsequently compared with all other runs in order to be differentiated. Furthermore, the exclusive patterns were examined to determine if a universal attractor could be attributed to a running movement. This led to these two main research questions:

Table 3: Research questions study 3

<table>
<thead>
<tr>
<th>Objective 3.1:</th>
<th>Can athletes be identified purely by their unique running style?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothesis 3.1:</td>
<td>Running athletes can be identified based on a unique running style.</td>
</tr>
<tr>
<td>Objective 3.2:</td>
<td>Is there a general attractor for the running motion and can the individuality of each runner be seen as a modification of such?</td>
</tr>
<tr>
<td>Hypothesis 3.2:</td>
<td>There is a general pattern for the running movement and individual deviations from it make each person unique.</td>
</tr>
</tbody>
</table>

The purpose of the final study in the current dissertation was to apply the attractor method to another popular cyclic movement: cross-country skiing. To accomplish this, the attractor method was used to analyze group and individual differences in the skating techniques of collegiate cross-country skiers at Northern Michigan University (NMU). Sixteen elite cross-country skiers from NMU were tested while skating with roller skis on a treadmill. They wore MEMS sensors on both wrists, on the lateral side of both of their ski boots (at ankle height), and one on their torso, which recorded acceleration and gyroscope data. They skate-skied for five minutes with a double-pole propulsion every second stride (V1) and another five minutes with a double-pole plan every stride (V2). These were randomly ordered and separated by a five-minute resting (wash-out) phase. The collected data was then mathematically converted into coordinate space using a self-programmed app to view the distance-time course of the limbs. This allowed the ski movement to be viewed in three planes: anterior-posterior, lateral-medial or left-right and vertical (up-and-down). This
experimental setup will enable sports scientists, trainers and athletes to use the attractor method to analyze movements in cross-country skiing in greater detail. The following application-related questions were assessed in the study:

Table 4: Research questions study 4

<table>
<thead>
<tr>
<th><strong>Objective 4.1:</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Can the attractor method be used to show the differences between two skating techniques used in cross-country skiing (V1 and V2)?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Hypothesis 4.1:</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>The attractor method can highlight the technical differences between both the V1 and V2 skating styles.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Objective 4.2:</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Can the attractor method be used to investigate the individual technique characteristics of a single skier?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Hypothesis 4.2:</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>The attractor method is capable of highlighting subtle differences in cross-country ski skating technique on an individual skier basis.</td>
</tr>
</tbody>
</table>

In the following chapters, the four studies that built up the content of this dissertation are presented in the original text version as published by the respective journal or book. The studies have been modified in so far that the references as well as page, table, figure and equation numberings have been adapted according to the layout of the present cumulative dissertation. The figures and tables are presented in the order of appearance in a corresponding directory at the end of the thesis. Further, all references in an alphabetical order can be found in the cumulative bibliography. If pages, tables, figures or equations from studies 1-4 are quoted throughout the thesis, the entries always refer to the version adapted for this layout. All above mentioned modifications have no influence on the content and the understanding of the individual articles. The author contributions of each study are visualized in chapter 10.
2 STUDY 1: The kinematics of cyclic human movement

PLOS ONE

Manfred M. Vieten & Christian Weich

Bibliographic reference:
RESEARCH ARTICLE

The kinematics of cyclic human movement

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OPEN ACCESS


Editor: Nizam Uddin Ahamed, University of Pittsburgh, UNITED STATES

Received: November 2, 2019
Accepted: February 17, 2020
Published: March 5, 2020

Peer Review History: PLOS recognizes the benefits of transparency in the peer review process; therefore, we enable the publication of all of the content of peer review and author responses alongside final, published articles. The editorial history of this article is available here: https://doi.org/10.1371/journal.pone.0225157

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Data Availability Statement: All data files are available from zenodo.org under the direct link http://doi.org/10.5281/zenodo.3518415.

Funding: AFF-grand "cyclic human motion - 2019" of the University of Konstanz. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: The authors have declared that no competing interests exist.
2.1 Abstract

Literature mentions two types of models describing cyclic movement—theory and data driven. Theory driven models include anatomical and physiological aspects. They are principally suitable for answering questions about the reasons for movement characteristics, but they are complicated and substantial simplifications do not allow generally valid results.

Data driven models allow answering specific questions but lack the understanding of the general movement characteristic. With this paper we try a compromise without having to rely on anatomy, neurology and muscle function. We hypothesize a general kinematic description of cyclic human motion is possible without having to specify the movement generating processes, and still get the kinematics right. The model proposed consists of a superposition of six contributions—subject’s attractor, morphing, short time fluctuation, transient effect, control mechanism and sensor noise, while characterizing numbers and random contributions. We test the model with data from treadmill running and stationary biking. Applying the model in a simulation results in good agreement between measured data and simulation values. We find in all our cases the similarity analysis between measurement and simulation is best for the same subjects – \( \delta_{\text{run same sub}} > 55\% \) and \( \delta_{\text{bike same sub}} > 64\% \). All comparisons between different subjects are \( 51\% > \delta_{\text{run different sub}} \) and \( 52\% > \delta_{\text{bike different sub}} \). This uniquely allows for the identification of each measurement for the associated simulation. However, even different subject comparisons show good agreement between measurement and simulation results of differences \( \delta_{\text{run}} = 6.7 \pm 4.7\% \) and \( \delta_{\text{bike}} = 5.1 \pm 4.5\% \).

2.2 Introduction

Bipedal gait, especially walking, has been the most decisive development of homo sapiens to surpass their ancestors and relatives (Bramble & Lieberman, 2004). In the past centuries further cyclic motions like swimming, cycling, rowing or skiing came along, to overcome natural obstacles, to facilitate traveling and then as leisure activities. Recently, cyclic motion descriptions have served as biological templates for developments in robotics together with developments in artificial intelligence (Kerscher, 2010). Although cyclic movements are performed a thousand-fold each day in everyday life, their underlying composition and structure is not fully understood. The kinematics of human cyclic motion seems rather simple at first glance.
Detailed observations display a repeating structure and some fluctuation producing similar but not identical repetitive cycles of movements (Weich et al., 2019; Williams, 1997). These changes often describe a transient effect at the start of the movement (Hurmuzlu, 1993; Hurmuzlu & Basdogan, 1994; Weich et al., 2019), as generally observed in dynamical systems (Alligood et al., 2000; Strogatz, 2015). Moreover, various perturbations alter the regularity of the ongoing movement and stride time dynamics (England & Granata, 2007; Hausdorff et al., 1995; Hausdorff, Zemany, Peng, & Goldberger, 1999; Spitzer, 1964). Dingwell and Kang (2007) describe these findings as ‘inherent biological noise’, being local instabilities (Dingwell & Cusumano, 2000) during movements like walking, without causing falls or stumbles, meaning that the subjects move ‘orbitally stable’. Nashner (1980) pointed out, that the described continuity after perturbations is retained by adjusting parameters of the present walking motion rather than recruiting a new motor pattern (p. 650).

Modern quantitative scientific endeavors to understand the mechanism behind the central movement trait already began as early as in the nineteenth century (Al-Zahrani & Bakheit, 2008). Describing cyclic motion most often is realized by selected specific body markers and their coordinate portrayal as function of time (Sehle et al., 2011). The classical gait parameters such as step length, step frequency, velocity as well as marker tracking from digitizing systems carry most of the information considered. With the advent of direct acceleration measurement further and subtler information, which coordinate explanation cannot deliver, can serve to describe cyclic motion. Coordinate data, however, can at least in principle, be generated from acceleration data by two consecutive integrations with respect to time. However, integration is a smoothing process, which makes it evident, that important information gets lost.

For this reason, we propose a mathematical model of the kinematic of the human cyclic motion based on acceleration data. It allows simulation of cyclic movement and comparison with measured data. We illustrate this model as a superposition of six mathematical terms covering the motion as a (1) limit-cycle attractor, (2) individual attractor morphing, (3) short time random fluctuation in form of “random walk”, (4) the transient effect describing initial oscillations around the attractor at the onset of the activity subsiding with increasing time, (5) a control process being activated when stride variations tend to exceed the morphed attractors’ boundaries, and (6) the influence of noise generated by the measurement device—accelerometers. Thus, this model allows extension of earlier findings specifically about the variability of subjects’
cyclic movement with its fixed and random components.

There exist two types of models describing human cyclic motion—theory driven and data driven (Janssen et al., 2008)—both with its own strong and weak aspects. For example, a theory driven model as described by Gerritsen, van den Bogert and Nigg (1995) gives insight into the working of seven muscle groups within the lower extremities. The necessity of keeping the model manageable, in the mentioned paper by using a 2-dimensional rigid body model, leads to deviations from the actual movement. On the other hand the data driven model of Janssen et al. (2008) was able to detect the influence of emotions onto the movement pattern. They applied deep machine learning by using artificial neural nets, allowing identification of subtle effects. While here the detection movement characteristics caused by emotions is nicely achieved, the specifics of the gait changes remained undetected. With the present paper we attempt a compromise, by not having to rely on anatomy and muscle function, but still trying to understand kinematic processes and the movement pattern quantitatively. A study on cycling at two different power outputs (150 W and 300 W) at a cadence of 90 rpm (Enders, von Tscharner, & Nigg, 2015) found differences in the muscle activities detected via EMG, while kinematic data stayed almost unchanged. This result together with the stability of the individual’s attractor over time and after rehabilitation (Broscheid et al., 2018; Byrnes et al., 2018) is motivation to examine the possibility to quantitatively describe movement without the knowledge of muscle activity.

The purpose of this paper is to precisely outline the kinematics of cyclic motion by establishing the necessary mathematical equations, which allow simulation. The method presented permits identifying subject specific movement constants. The testing of model and method is done on two classical cyclic motions: running (on a treadmill) and (stationary) biking.
2.3 Method

The first section “Model” of this paragraph is devoted to the details of our model. The six contributing terms are specified with their deterministic and probabilistic components. Following in the section “Model’s characteristic constants” we show how \( \delta M \), the mean distance between two attractors, is calculated and how this parameter allows determination of the model’s characteristic constants. To see how measurements are fitted into to model the section “Data handling” makes the connection between the raw acceleration data and the specific input format to the model. One of our objectives is to quantify the similarity/dissimilarity of an attractor compared to another attractor, which is not influenced by the transient effect and by morphing, changing one attractor into another. Such an attractor we call a super attractor. Its construct is given in the section “Super attractor” and used in the section “Similarity analysis” to quantify how similar the super attractor is compared to a tested one. In the section “Separating the transient effect form morphing” the super attractor is used again to achieve the separation. In the section “Simulation” some settings are specified and a link on the internet to the used computer apps is given. Finally, the necessary information on the “Subjects”, the “Equipment”, the “Running data” and the “Cycling data” is presented.

Model

We construct the full acceleration \( \vec{K}(t) \) as a superposition of the six terms

\[
\vec{K}(t) = \vec{A}(t) + \vec{M}(t) + \vec{F}(t) + \vec{T}(t) + \vec{C}(t) + \vec{N}(t)
\]

1. \( \vec{A}(t) \) the Limit-Cycle-Attractor, a constant acceleration pattern being repeated with every cycle.
2. \( \vec{M}(t) \) attractor Morphing, which allows minor deviations from the actual attractor values.
3. \( \vec{F}(t) \) short time Fluctuation in form of a “random walk”.
4. \( \vec{T}(t) \) Transient effect, which can be present at the start and decreases rapidly.
5. \( \vec{C}(t) \) Control mechanism, kicking in when actual accelerations deviate too much from the morphed attractor.
6. \( \vec{N}(t) \) Noise caused by the accelerometers.
1. Limit-Cycle-Attractor $\hat{A}(t)$ can be regarded as the average of all cycles. This, however, is an idealized definition, which cannot fully be met, since this would call for averaging of an infinite number of cycles. Instead, we approximate the attractor by a finite number of cycles, which for later examples we chose the number of complete cycles within a specified minute of the data collection.

\[
\frac{\vec{K}}{\tau_j}(t) = \frac{1}{n} \sum_{i=1}^{n} \vec{a} \cdot (i \cdot \tau_j)
\]  

is a closed line in 3D acceleration space with $\vec{a}$ the measured acceleration and $j$ being the number of consecutive data points within an attractor. Such an approximated attractor is characteristic for each individual (Broscheid et al., 2018; Byrnes et al., 2018). The actual calculation starts with dividing each data set into one-minute sections and calculation of the attractors (Vieten et al., 2013). There is one important methodological difference, however. Instead of adding the cycles, which have different numbers of data points in temporal order, we describe each cycle as consisting of a fixed data point number $n$. This is achieved through spline approximation. The number $n$ stands for the mean number of data points of all complete cycles within a one-minute interval. So, we treat each cycle as lasting an identical time interval equal to the mean cycle duration. Afterwards we add up all cycle values for each of the $n$ points and divide them by the number of cycles. The results represent mean values of the one-minute data sets preserving the original sampling frequency, while still containing the influence of morphing, random walk, transient effect and the control mechanism. The data set least influenced serves as attractor to compare all others with. Appropriate attractors are those for which time $t \gg t_T$ (transient time, explained below).

2 Adaptation in comparison to the original text version: Equation 2, differing from the introductory text, does not describe the actual limit-cycle-attractor $\hat{A}(t)$, but the original definition based on (Vieten et al., 2013), labelled with $\vec{K}(t)$, containing all six components described in the section 'model'.
2. A time-dependent individual attractor morphing $\bar{M}(t)$ is described as the attractor change from start $t_s$ to end $t_E$ minute by minute. The equation is of heuristic nature. It must be capable of describing the changes of a given attractor and its development to the final attractor as a function of time. We take care of this process by taking attractor approximations at beginning $\bar{K}(t_s)$ and end $\bar{K}(t_E)$ and describe the morphing of the two attractor approximations, introducing the three dimensionless constants $a_0$, $a_1$, $a_2$, by

$$
\bar{M}(t) = \left(\bar{K}(t_s) - \bar{K}(t_E)\right) \cdot a_0 \cdot \left\{ \frac{(t_e-t)}{t_E} + a_1 \cdot \sin\left(a_2 \cdot 2\pi \frac{(t_E-t)}{t_E}\right) \right\}
$$

(3)

Important to mention: The morphing is small compared to attractor differences between individuals.

3. Fluctuation $\bar{F}(t)$ in the form of a “random walk”. These are changes around a morphed attractor described with the iteration

$$
\bar{F}(t) = \bar{F}\left(\frac{l}{f_S}\right) = \bar{F}\left(\frac{l - 1}{f_S}\right) + RN[0, \sigma_{RW}] \cdot \begin{pmatrix}
\sin(\vartheta(l)) \cdot \cos(\varphi(l)) \\
\sin(\vartheta(l)) \cdot \sin(\varphi(l)) \\
\cos(\vartheta(l))
\end{pmatrix}
$$

(4)

Here, $l$ is the data number. An aberration from the attractor can happen in any direction. We describe this using the angles $\vartheta$ and $\varphi$. Their actual values are random having a uniform distribution on the sphere with the polar and azimuthal angles:

$$
\vartheta(l) = RU[0, \pi] \\
\varphi(l) = RU[0, 2\pi]
$$

(5)

$RU[\alpha, \beta]$ represents random generation with a uniform characteristic within the interval $[\alpha, \beta]$. With this definition the standard deviation of the random walk depends on the
sampling frequency $f_S$. Since the random walk must not be dependent on the specifics of a measurement—the sampling frequency $f_S$—we introduce a parameter $\phi$ (random walk’s strength), which does not change with the sampling frequency.

$$\sigma_{RW} = \frac{f_S}{10^6} \cdot \phi \quad (6)$$

The factor $10^6$ was introduced for convenience. For simulating the movement $\phi$ together with $\tilde{C}(t)$ (see below) must be chosen must be chosen to reproduce the statistical spread of the data around the attractor.

4. The controlling mechanism $\tilde{C}(t)$, respectively the vector component $C_k(t)$, is kicking in when the distance to the morphed attractor’s coordinates passes the border $b_k$

$$b_k(j) = b \cdot \frac{\sigma_k(j)}{\langle \sigma_k \rangle} \quad (7)$$

at attractor point $j$. Here $b$ is the controlling constant and $\sigma_k(j)$ the attractor’s standard deviation, which is divided by the average of the attractor’s deviation $\langle \sigma_k \rangle$. This takes care of the changing width of the acceleration bundle. The correction term, being activated at time $t_b$, is modeled as

$$C_k(t, t_b) =$$

$$- \int_{t_b}^{t} RN[1, \sigma_M](t') \cdot A_k \cdot \frac{(t' - t_b)}{\tau} \cdot e^{-\frac{(t' - t_b)}{\tau}} \cdot \text{sign}(F_k(t_b)) \cdot \Theta(t_M + t_b - t') \cdot dt' \quad (8)$$

With $\text{sign}(...)$ being the signum and $\Theta(...)$ the step function. We set the maximal acceleration change to $\tau = 80 \text{ ms}$ analogous to the style of a muscle’s timely response (Buchthal & Schmalbruch, 1970) with acceleration effectively lasting $t_M = 4 \cdot \tau = 320 \text{ ms}$, to obtain
\[ b_k = \int_{t_b}^{t_M+t_b} A_k \cdot \frac{t - t_b}{\tau} \cdot e^{-\frac{t-t_b}{\tau}} \, dt \]  

(9)

\( b_k \) is the acceleration necessary to get back precisely onto the morphed attractor values. This holds true for

\[ A_k = \frac{b_k}{\tau - (\tau + t_M) \cdot e^{-\frac{t_M}{\tau}}} \]  

(10)

\( RN[1, \sigma_M](t) \) represents a a normally distributed random element introducing some deviation from a perfect working controlling mechanism.

5. The transient effect \( \vec{T}(t) \) is a temporary oscillation around the attractor at the beginning of a cyclic movement. The starting value of the oscillation might be very individual, specific to the subject, and having a part of the starting value occurring by sheer chance. We model the deviation as the solution of a damped harmonic oscillator, where the transient term can be viewed as the departure from the morphed attractor

\[ \vec{T}(t) = \sum_{h=1}^{m} \biggl( \vec{T}_h \cdot \cos(h \cdot \omega \cdot t + \delta_h) \biggr) \cdot e^{-\frac{t}{t_\tau}} \]  

(11)

with \( \omega = \frac{2\pi}{t_A} \), \( t_A \) being the average time of one cycle within the one-minute interval \( \Delta t \). \( \delta_h \) is, which within a simulation is chosen randomly being any number between zero and \( 2\pi \). \( h \) specifies the number of harmonics contributing, with \( m \) being the highest one. The maximal harmonic is identified from the Fourier transform of a subject’s movement. \( t_\tau \) denotes the time for the transient effect decreasing to \( e^{-1} \). The transient effect averaged over the \( n^{th} \) minute is
\[ \langle \vec{T}(n \cdot \Delta t) \rangle = \frac{1}{\Delta t} \cdot \int_{(n-1)\Delta t}^{n\Delta t} \left\{ \left[ \sum_{h=1}^{m} \vec{T}_h \cdot \cos(h \cdot \omega \cdot t + \delta_h) \right] \cdot e^{\frac{-t}{\tau}} \right\} dt \]  

\[ = (\vec{T}_\parallel + \vec{T}_\perp) \cdot e^{\frac{-n\Delta t}{\tau}} \]  

Here and below \( \parallel \) stands for the part of the vector pointing in the direction of the combined vectors of \( \vec{T}(t) \) and \( \vec{M}(t) \). \( \perp \) indicates the vector parts perpendicular to the mutual direction.

6. When simulating the kinematics and comparing it with real life data, we need to include the measurement error – noise \( \vec{N}(t) \) - caused by the sensor characteristics. It can be obtained directly from measuring the output signals of the sensors at rest. The signal of an accelerometer is, subtracting the values caused by the earth’s gravitational field, modeled as white noise.

\[ \vec{N}(t) = RN[0, \sigma_{Sensor}] \cdot \begin{pmatrix} \sin(\vartheta_s(t)) \sin(\varphi_s(t)) \\ \sin(\vartheta_s(t)) \cos(\varphi_s(t)) \\ \cos(\vartheta_s(t)) \end{pmatrix} \]  

Here \( RN \) stands for a random normally distributed contribution with a mean value of \( 0 \, m/s^2 \) and a standard deviation \( \sigma_{Sensor} \), which is the characteristic of the specific sensor. \( \vartheta_s \) and \( \varphi_s \) are randomly chosen to get a uniform distribution on the unique sphere. \( \sigma_{Sensor} \) is calculated using equation (13) and taking \( \vec{N}(t) \) from the data recording of the sensors at rest.
Model’s characteristic constants

The main parameter for checking the model’s validity is $\delta M$. It is the average distance between two data sets (Vieten et al., 2013) and is calculated using Eq (1) by

$$
\delta M = \frac{1}{v} \sqrt{\langle (\bar{K}(t) - \bar{K}(t_E))^2 \rangle}
$$

$$
= \frac{1}{v} \sqrt{\langle (\bar{A}(t) + \bar{M}(t) + \bar{F}(t) + \bar{T}(t) + \bar{C}(t) + \bar{N}(t) - \bar{A}(t_E) - \bar{M}(t_E) - \bar{F}(t_E) - \bar{T}(t_E) - \bar{C}(t_E) - \bar{N}(t_E))^2 \rangle}
$$

$$
\approx \frac{1}{v} \sqrt{\langle (\bar{T}(t) + \bar{M}(t) - \bar{T}(t_E))^2 \rangle}
$$

$$
= \frac{1}{v} \left[ (T^\parallel(t) + M^\parallel(t) - T^\parallel(t_E)) \right]
$$

$$
= \frac{1}{v} \cdot T^\parallel \left[ e^{\frac{-t}{T}} - e^{\frac{-t_E}{T}} \right] + a_0 \cdot \left\{ \left( \frac{t_E - t}{t_E} \right) + a_1 \cdot 2\pi \left( a_2 \cdot \frac{(t_E - t)}{t_E} \right) \right\}
$$

Here $\bar{A}(t) \equiv \bar{A}(t_E)$ by definition of an attractor as being identical at any cycle. The fluctuation together with the correction term do have almost identical averaged contributions close to zero at the different one-minute time intervals. The noise has contributions almost completely cancelling out within one minute because of its normal distributed character having a mean of zero. Therefore, the remaining input comes from the transient effect and the attractor morphing. We can calculate the length of the three lasting vectors. The remaining terms are the parallel contributions, all lying in the same direction at a given time, which can be written as a sum scalars. The subsequent equation allows us to write $\delta M$ depending on 5 constants $T^\parallel, t_T, a_0, a_1, a_2$, which are specified by curve fitting of the measurements. We use the software CurveExpert Professional 2.6.5, which uses the Levenberg-Marquardt algorithm providing the non-linear curve-fitting. While the three constants on the right describe the highly individual subject and task dependent morphing, the two constants on the left approximate the transient oscillation contributing to $\delta M$ at the beginning of a cyclic movement. $t_T$ depicts the time until the oscillation decreases to $1/e$ of its original value $T$. The oscillation is negligible if $t_T \geq t_E$ (measuring time) since than the two exponential functions are almost equal to 1 resulting in these terms cancelling out. The values of the morphing and the transient effect do mix, which does not allow these two effects to be separated.
in all cases. Fortunately, there is a method to separate these two effects, which will be explained below. Altogether, we now have the nine constants $\phi$, $t_E$, $t_T$, $t_A = \frac{2\pi}{\omega}$ $T_\parallel b$, $a_0$, $a_1$, $a_2$ determining our model. All definitions and the respective calculations/approximations are given to allow simulation of cyclic motion with the help of the attractors and the constants gained from the measured data. These simulations are naturally not identical to the original data, since the algorithm contains contributions of random processes.

**Data handling**

Since further analysis required the collected 60-minute data block to be divided into 60-second intervals, a file splitter was applied to produce suitable single datasets. A raw data text-file contained thirteen columns: time and the acceleration as well as the gyroscope data in x, y and z direction for the left and the right foot, respectively. Afterwards an app called “Attractor”, programmed with MATLAB was used to calculate the attractor data of every one-minute data set. Each attractor dataset contained 25 x n velocity/cadence-normalized data points: t, x\text{left foot}, y\text{left foot}, z\text{left foot}, x\text{right foot}, y\text{right foot}, z\text{right foot}, their standard deviations, standard errors, and gyroscope data. The functionality of the Attractor App is based on the attractor method developed by Vieten et al. (2013) with the alteration of the attractor building process described above. The attractors were normalized for velocity in running and cadence (normalization factor $v = \text{cadence}/10$) for biking.

**Super attractor**

A super attractor is by definition the average of all attractors of one subject, with the exclusion of any attractors that are to be compared to the super attractor. Also, no attractor influenced by the transient effect (usually those calculated from the data of the first 10 minutes of a measurement) is included. Specifically, for this study the super attractor was calculated for each participant from the collection of the final 50 minutes of each run independent of the data to be analyzed.
Similarity analysis

For this procedure each attractor is recalculated having 500 data points by adjusting the sampling frequency using spline approximation. To find out how similar two movements are, we calculated the recognition horizon around each single attractor point, which is defined as the surface area at a distance equal to five standard deviations away from the attractor point. A test attractor is checked point to point if lying in- or outside the recognition horizon of the first attractor using another MATLAB procedure (Fig 1).

![Figure 1: Schematic two-dimensional depiction of the three-dimensional recognition horizon (red) and compared attractor (blue).](image)

Each measured or simulated minute over all running or cycling sessions (5 x 60 minutes) was checked against the respective super attractor. The similarity rate is defined as the percentage of data points lying within the recognition horizons.

Separating the transient effect from morphing

To exclude the influence of the morphing as much as possible, we calculated a super attractor from 5 independent 1-hour-runs of each individual taken about 5 months before the actual measurements for running. For biking, as we did not have the data from months before, a super attractor was created out of four datasets to compare with the fifth one.
Since our hypothesis was that an attractor is stable only within a given interval, the super attractor represents just one possible attractor configuration. It is important to note that these super attractors are independent of the 60 minutes data sets to be examined. Therefore, with the exception of the first minutes being influenced by the transient effect, the comparison should display results not varying much. And finally, the δM can be approximated by

$$\delta M_{\text{without morphing}} = c_0 + c_1 \cdot t + c_2 \cdot \exp\left(\frac{-t}{t_f}\right)$$  \hspace{1cm} (15)

As before, the constants are approximated applying the Levenberg-Marquardt algorithm through the software CurveExpert Professional 2.6.5. Here $c_0$ represents the strength of morphing. $c_1$ is the linear variation and is expected to be very small, since the distance between a super attractor and the attractors of a measurement should have very little variation with the exception of when the transient effect is active. Last $c_2$ denotes the strength of the transient effect.

**Simulation**

For the simulation we created an app called “TrackSimulator” (accessible at http://www.uni-konstanz.de/FuF/SportWiss/vieten/CyclicMove/), available as Windows and macOS versions. It was created within MATLAB and is available as stand-alone solution without the need to install the MATLAB program. The app includes all the algorithms described above. To obtain the simulation the attractors of the tested subjects and their individual nine constants $\phi \ t_E \ t_T \ t_A \ T_{\parallel} \ b \ a_0 \ a_1 \ a_2$ serve as input for the app. We set the number of harmonics = 2 within the Eq (11), because those harmonics the majority of the signal’s strength. Using the phase of the measurement within the simulation would give a good conformity between measurement and simulation. However, our first priority is about finding out about the variability of the cyclic motions. Therefore, the phase of the transient effect was chosen randomly.
Subjects

A total of ten athletes, six female and four males, were tested in summer 2019. The running data (n = 5) were collected in Kreuzlingen, Switzerland (Nationale Elitesportschule Thurgau) whereas the cycling measurements (n = 5) took place at the University of Konstanz, Germany. All runners were active experienced recreational athletes. None had suffered any present injury, which could have impeded their performance. The cyclists were recruited from the local pool of university students. The only prerequisites were to be aged 18 years or older and able to run 60 minutes without reducing their initial pace or cycling at a moderate wattage over 60 minutes as regulated by their age, weight and training level (Kindermann, 1987), respectively. All participants were requested to fill out and sign an informed consent. The study was approved by the local Ethical Committee of the University of Konstanz, Germany under the RefNo: IRB19KN10-005.

Equipment

To collect the necessary raw accelerometer data, two inertial sensors (RehaWatch by Hasomed, Magdeburg, Germany) were attached to both ankles by a hook-and-loop fastener during the runs; and on the proximal frontal part of the tibia (facies medialis) during the cycling tests. The sensors, MEMS—micro-electro-mechanical-system, have a size of 60x35x15 mm and weigh 35 g each. They function as a triaxial accelerometer, which we set up to a measurement interval of ±8 g, and a triaxial Gyroscope with up to 2000°/s. The sampling rate was set to 500 Hz. Acceleration of the feet was measured in three dimensions (x, y, z) with data saved to a smartphone (Samsung Galaxy J5) using the app RehaGait Version 1.3.9 programmed by Hasomed (Magdeburg, Germany). All runs were performed on a treadmill (9500HR by Life Fitness, Unterschleißheim, Germany). The cycling measurements were undertaken on a cycle ergometer (ergoselect200, Ergoline, Bitz, Germany).

Running data

The first session started with a short 5-minute warm up phase to get familiar with the treadmill and to determine an easy running pace associated with a BORG-scale of 3 (Wilson & Jones, 1989) (table 5).
**Table 5: Running speed of the subjects.**

<table>
<thead>
<tr>
<th></th>
<th>Subject 1</th>
<th>Subject 2</th>
<th>Subject 3</th>
<th>Subject 4</th>
<th>Subject 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Running speed</td>
<td>10 km/h</td>
<td>11 km/h</td>
<td>10 km/h</td>
<td>8.5 km/h</td>
<td>8.7 km/h</td>
</tr>
</tbody>
</table>

**Table 6: Power output of subjects in biking.**

<table>
<thead>
<tr>
<th></th>
<th>Subject 6</th>
<th>Subject 7</th>
<th>Subject 8</th>
<th>Subject 9</th>
<th>Subject 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cadence</td>
<td>90 rpm</td>
<td>60 rpm</td>
<td>65 rpm</td>
<td>60 rpm</td>
<td>60 rpm</td>
</tr>
<tr>
<td>Power output</td>
<td>130 W</td>
<td>60 W</td>
<td>80 W</td>
<td>50 W</td>
<td>80 W</td>
</tr>
</tbody>
</table>

The chosen running speed remained stable throughout all following test sessions each lasting 60 minutes. The participating athletes repeated the testing protocol in a time frame of approximately four weeks consisting of five testing days separated by at least 24 hours. The measurements were received from tri-axial accelerometers by a smartphone placed on a desk beside the treadmill to ensure undisturbed reception. Before the actual run, the participants set up the treadmill at 1% inclination (to simulate wind resistance) and their individual speed while waiting on the collateral standing area close to the treadmill belt. Once the chosen speed of the belt was reached the tester counted down from three to one before starting the data collection on the smartphone. At the same time, the runner jumped onto the treadmill belt and started immediately with running at the chosen pace over 60 minutes. This jumping movement, lasting approximately one second, was cut out of the data during the data management process, as it was a nonrunning-specific movement.

**Cycling data**

Within four weeks, all cyclists repeated the testing protocol five times. Before the initial test day, the research group calculated the power and selected an appropriate seat position. All participants were tested at their preferred cadence (rpm = repetitions per minute), which the participants were able to hold within the interval of ±3 rpm over 60 minutes. Their power output conformed with an easy endurance workout and was defined using the athletes’ age, weight and training level (Kindermann, 1987) (table 6).
On each test day, the cyclists adjusted the seat and the handlebars as determined. The research assistant advised the athlete to hold the seating position and the cadence as stable as possible. The data collection was started by the tester immediately after the start signal caused the participant to pedal.

2.4 Results

All input, measured data and simulation results, had a sampling frequency of 500 Hz. Further procedures, including generating graphs, were done after filtering with a ‘triple F low pass filter’ (Vieten, 2004) with a cutoff frequency of 10 Hz.

For the simulation, we used the constants $t_T$, $t_A = \frac{2\pi}{\omega}$, $T_\parallel$, $a_0$, $a_1$, $a_2$ taken from the measurements displayed below. The duration of simulation $t_E = 60\ min$ was identical to the measurement’s time. The random walk’s strength was set $\phi = 100$ and the controlling constant at $b = 5$.

A graphic comparison between measurement and simulation gives a first impression of the model’s power (Fig 2). From $\delta M$ of the measurement we get the five constants $T_\parallel$, $t_T$, $a_0$, $a_1$, $a_2$. They are depending on the subject and on the specific movement. For our measurements we find the intervals of Table 7. Similarity rates between measurements and simulation do show differences. This is expected since our model, in addition to containing deterministic parts, has random components as well. Important here is that the similarity analysis for running yields a gap between 50 and 56 %, clearly separating same from different subject comparisons (Fig 3).

![Figure 2: Measured data (blue) and simulation results (red) of the first run of subject three.](image-url)
All comparisons, of measurements or simulations, between same subjects lie above the gap, comparisons between different subjects lie below. For biking there is the same situation with a gap of 52 to 64 % (Fig 4) clearly separating same from different subject comparisons. As before, all same subject comparisons lie above the gap, different subject comparisons below.

Values of $\delta M$ –Eq (14)– are influenced by morphing and the transient effect. A typical progression with both factors influencing $\delta M(t)$ is shown in Fig 5. In the first few minutes, the transient effect causes an increase/decrease, while morphing with its more moderate decline is visible afterwards. The differences between the measurement (blue) and the simulation (red) are caused by the transient effect and the “short time fluctuation”. Here the starting conditions are largely random, causing differences at the beginning.

The difference between measurement and the simulation are caused by the transient effect and the “short time fluctuation”. Here the starting conditions are largely random, causing differences at the beginning. The morphing of a specific measurement is imprinted into the simulation values via the Eq (3). A morphing effect is visible, if the analyzed minutes are from one uninterrupted measurement. The comparisons with the super attractor calculated from data independent of the actual numbers display random changes and the transient effect, but no morphing (Fig 6). Those data can be approximated using Eq (15), which allows calculation of the transient effect largely without the influence of morphing. $\delta M$ does not vary much with the only remarkable deviation at the beginning and up to about the 10$^{th}$ minute. Fig 6 shows $\delta M(t)$ for the five runs of subject 3, a representative where a substantial transient effect is prominently visible. Other subjects, especially the cyclists, show fewer or no exponential behavior at the beginning. Table 8 provides the time $t_T$ in minutes until the transient effect (TE) settles down to $e^{-1}$ of its initial value. This takes 4.3 minutes on average, where the cases without the transient effect are excluded. The absolute height of $\delta M$ depends on the attractor’s similarity compared with the independent super attractor. The following graphs, runs (Fig 7) and bike trials (Fig 8), show the mean and the standard deviation of $\delta M$ for all subjects. The calculations are based on minutes 11 to 60, excluding the data influenced by the transient effect. Therefore, these values are a direct measure for morphing. For running $\delta M$ is in a range 2 to 5 m/s$^2$. Cycling displays values between 7 and 14 m/s$^2$ with one exception of a striking low $\delta M$ of about 1–1.4 m/s$^2$ for subject 10.
Table 7: Overview of characteristic constants.

<table>
<thead>
<tr>
<th>Constant</th>
<th>Transient effect’s strength</th>
<th>time for the transient effect decreasing to $T e^{-1}$</th>
<th>morphing’s strength</th>
<th>morphing’s modulation strength</th>
<th>morphing’s nonlinearity multiplier</th>
</tr>
</thead>
<tbody>
<tr>
<td>Running</td>
<td>-3–10</td>
<td>Individually given in table 8</td>
<td>1–8</td>
<td>-0.4–0.5</td>
<td>-0.3–1.8</td>
</tr>
<tr>
<td>Biking</td>
<td>0–10</td>
<td></td>
<td>0.5–13</td>
<td>-0.3–0.3</td>
<td>0.3–4.2</td>
</tr>
</tbody>
</table>

Figure 3: Similarity rate of running measurements (triangle pointing right) and simulations (triangle pointing left).

2.5 Discussion

The purpose of this paper was to find a quantitative description of cyclic motion with the capacity to simulate individuals’ characteristic movement. A model was proposed consisting of six contributing parts. Individual attractor, morphing, short time fluctuation, transient effect, control mechanism and sensor noise. Simulations based on this model showed the same distinctive variations as the measured data. In all cases the similarity analysis of same subjects produced higher results $\delta_{run}^{same sub} > 55 \%$ and $\delta_{bike}^{same sub} > 64 \%$ compared with different subject combinations $51 \% >$
\( \delta_{\text{run}} \) and 52 \( \% > \delta_{\text{bike}} \). Measurements of the respective simulations are clearly identifiable, confirming the model’s suitability for describing cyclic motion. The nine constants together with the subject’s attractor approximations are characteristic for a person’s movement and the influence of the recording sensors.

\[ \text{Figure 4: Similarity rate of biking measurements (triangle pointing right) and simulations (triangle pointing left).} \]

As known from previous studies (Broscheid et al., 2018; Byrnes et al., 2018) the influence of morphing and transient effect is small compared with the differences between individuals. While morphing is present in all trials, the transient effect is not observable in all cases (20 of 25 cases for running, 8 of 25 cases for biking). For biking, the transient effect is less prominent compared to running. We suspect the fixation of the legs with the foot connected to the pedal and the hip very much fixed onto the saddle, there is limited freedom in movement variation. The tibia position and its associated acceleration is often settled onto the attractor from the start onwards. A different situation is seen in running, where the kinematic chain is unfixed near the location of the accelerometer at the distal end of the tibia. Here the probability to start a movement close to the subject’s attractor, resulting in no visible transient effect, is small. Interestingly, the most experienced runners show the least transient effect.
The comparison of a subject's attractors of a 1-hour measurement to an independent *super attractor* allows approximation of the magnitude of morphing. The maximal difference between attractors from independent measurements of one subject is restricted by the maximal possible morphing. Morphing can deform an attractor in many different ways, which most probably results in $\delta M$'s of comparable values. Therefore, results as shown in Figs 7 and 8 might represent good approximations of typical morphing magnitudes. Still, the determination of the attractor remains a challenging issue. In mathematical systems, like the famous "Lorenz map", the attractor is reached after the transient effect subsided. There, either a stable regular attractor is reached or a strange one is seen. Here, although data of the cyclic motion never completely reaches regularity, neither is the behavior completely chaotic. The regularity is, as mentioned before, good enough to discriminate between individuals. Still the question remains, how to rate the attractors' differences, when attractor approximations are calculated by averaging the cycles of different time intervals. Does it simply mean that when doing the averaging over longer time periods these differences will almost completely vanish? Or, does it mean that attractors are changing with time, even if these changes are small? So far, we do not have enough data to answer this question with certainty. However, from the results above we suggest that the second statement is more likely.
There is a theoretical argument for this statement as well. While developing the mathematical description of cyclic motion, our first approach was without morphing. The idea was to have an attractor not dependent on time and the fluctuation based on a “random walk” characteristic only. This construct, however, did not allow describe the full data variability.

From a sport scientific view, the underlying components of the model are of particular interest in cyclic sports like running, cycling, swimming or rowing. Earlier work reports differences in subject-specific alternations in running patterns throughout prolonged activities like marathon running (Clermont, Benson, Edwards, Hettinga, & Ferber, 2019). The latter authors state that competitive runners show a greater consistency of their subject-specific movement pattern compared to their recreational opponents, whose gait

![Graph](image.png)

*Figure 6: Five runs of subject 3 compared to the subject’s independent super attractor. The lines represent the approximation as of Eq (15).*

characteristics become significantly atypical halfway through the race. Further Clermont, Benson, Osis, Kobsar and Ferber (2019) have demonstrated with their approach the ability to differentiate sex-and training level-specific subgroups based on acceleration data. An athlete with an extensive running experience combined with an increased mileage performs necessarily a higher number of strides leading to a more
implanted and efficient movement pattern (Barnes & Kilding, 2015).
Thus, it can be assumed that the duration of the transient effect ends sooner combined
with less deviations of the actual attractor contributed by the morphing effect. Should
momentary accelerations still deviate from the morphed attractor, it can be expected
that the control mechanism kicks in much sooner in athletes with a long-term training
history. To check the mentioned expectations further application studies, have to be
conducted. Altogether our model is capable describing cyclic motion quantitatively.
Given the individual’ attractor approximations and the subject specific constants, but
the simulation is specific for the subject’s particular movement.
In addition, there are other aspects needing further attention. One is establishing a
threshold for the similarity analysis to define the percentage when recognition is
achieved. Many more measurements of a specific cyclic movement should allow
determination of a suitable number by using the median method described by Vieten
et al. (2013). Another limitation of the current approach is the focus on calculating δM,
which depends on 𝑇̅_𝑖(𝑡) + 𝑀̅_𝑖(𝑡), the parallel components only. Analyzing the full
expression 𝑇̅(𝑡) + 𝑀̅(𝑡) might allow further insight.

2.6 Conclusion
This paper is a “proof of concept” showing cyclic motion can be described with the
mathematical model introduced. Moreover, the simulation based on the developed
model is capable of generating numbers displaying the same structure and behavior
as the measurement.

Table 8: The time tT [min] by which the transient effect (TE) reduces to e−1 of its start value.

<table>
<thead>
<tr>
<th>Sub</th>
<th>Run 1</th>
<th>Run 2</th>
<th>Run 3</th>
<th>Run 4</th>
<th>Run 5</th>
<th>Sub</th>
<th>Bike 1</th>
<th>Bike 2</th>
<th>Bike 3</th>
<th>Bike 4</th>
<th>Bike 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub 1</td>
<td>1.0</td>
<td>5.1</td>
<td>3.9</td>
<td>No TE</td>
<td>No TE</td>
<td>Sub 6</td>
<td>No TE</td>
<td>No TE</td>
<td>No TE</td>
<td>No TE</td>
<td>No TE</td>
</tr>
<tr>
<td>Sub 2</td>
<td>5.0</td>
<td>No TE</td>
<td>No TE</td>
<td>5.0</td>
<td>No TE</td>
<td>Sub 7</td>
<td>No TE</td>
<td>No TE</td>
<td>No TE</td>
<td>No TE</td>
<td>No TE</td>
</tr>
<tr>
<td>Sub 3</td>
<td>9.7</td>
<td>10.0</td>
<td>5.1</td>
<td>9.0</td>
<td>12.9</td>
<td>Sub 8</td>
<td>3.4</td>
<td>4.3</td>
<td>3.4</td>
<td>2.8</td>
<td>3.5</td>
</tr>
<tr>
<td>Sub 4</td>
<td>1.7</td>
<td>1.8</td>
<td>0.9</td>
<td>5.5</td>
<td>1.0</td>
<td>Sub 9</td>
<td>No TE</td>
<td>No TE</td>
<td>No TE</td>
<td>No TE</td>
<td>No TE</td>
</tr>
<tr>
<td>Sub 5</td>
<td>1.9</td>
<td>2.8</td>
<td>3.7</td>
<td>2.3</td>
<td>3.5</td>
<td>Sub 10</td>
<td>No TE</td>
<td>8.2</td>
<td>1.5</td>
<td>1.4</td>
<td>No TE</td>
</tr>
</tbody>
</table>
Figure 7: All 5 runs of all 5 subjects compared to their personal, but independent super attractor for minutes 11 to 60.

Figure 8: All 5 bike trials of all 5 subjects compared to their personal, but independent super attractor for minutes 11 to 60.
Applications are conceivable in the areas medical diagnostics, performance assessment, subject recognition, and robotics. For diagnostics, our group has previously developed and used a fatigability scale for multiples sclerosis patients (Sehle et al., 2011; Sehle, Vieten, Mündermann, et al., 2014). The new model however, allows description of the transition between normal and fatigability conditions more precisely by considering morphing. In terms of performance assessment, the results of Figs 7 and 8 suggest morphing’s magnitude is different depending on the specific subject. This might be correlated to athletes’ performance levels, using stable running patterns throughout prolonged physical activities. Further, it might allow deeper insight into the dependencies of parameters such as gender, training history and anthropometric attributes. Figs 3 and 4 – the arrows above the gap—show with the help of the similarity rate, that it is possible to find measurement/simulation combinations belonging to the same subject. This fact and some preliminary analyses suggest subject recognition is possible though attractor comparison. Here the attractor of a measurement is compared with a database of attractors. Finally, bipedal robots’ movement might profit from our model by comparing the specific values of the characteristic constant, as well as the specific form of the attractors between humans and robots.

2.7 Acknowledgments

We thank all subjects who participated in the study.
3 STUDY 2: Transient effect at the onset of human running

BIOSENSORS

Christian Weich, Manfred M. Vieten & Randall L. Jensen

Bibliographic reference:
3.1 Abstract

While training and competing as a runner, athletes often sense an unsteady feeling during the first meters on the road. This sensation, termed as transient effect, disappears after a short period as the runners approach their individual running rhythm. The foundation of this work focuses on the detection and quantification of this phenomenon. Thirty athletes ran two sessions over 60 min on a treadmill at moderate speed. Three-dimensional acceleration data were collected using two MEMS sensors attached to the lower limbs. By using the attractor method and Fourier transforms, the transient effect was isolated from noise and further components of human cyclic motion. A substantial transient effect was detected in 81 % of all measured runs. On average, the transient effect lasted 5.25 min with a range of less than one minute to a maximum of 31 min. A link to performance data such as running level, experience and weekly training hours could not be found. The presented work provides the methodological basis to detect and quantify the transient effect at moderate running speeds. The acquisition of further physical or metabolic performance data could provide more detailed information about the impact of the transient effect on athletic performance.

Keywords

attractor method; kinematics of human cyclic motion; motion analysis; transient effect; accelerometer
3.2 Introduction

In general, human motion, even the movements which are repeated many thousand times, e.g., by athletes, cannot be called absolutely consistent and stable (Bernstein, 1967; Hatze, 1986). No single movement is like any other and they are always characterized by a high degree of individuality (Weich & Vieten, 2020). Beyond the actual movement, it is also apparent that changes in movement patterns have an influence on the subsequent motion kinematics and thus must be highly controlled and regulated by the body and the brain, respectively. Most obvious is the change from a resting situation like sitting to physical activity (Kerr, Durward, & Kerr, 2004; Kerr, Pomeroy, Rowe, Dall, & Rafferty, 2013) or the change between two forms of movement, like from walking to running and back (Diedrich & Warren, 1995; Segers, Aerts, Lenoir, & De Clercq, 2006) or cycling to running in triathlon (Bonacci, Chapman, Blanch, & Vicenzino, 2009; Millet & Vleck, 2000; Weich et al., 2019). Weich et al. (2019) showed in a triathlon study, not only that the transition run after cycling showed deviating behavior over the first minutes of the session, but also from the control condition, an isolated 5000 m run. Either way, athletes often sense an irregular or uneven way of running at the onset of their exercise or in these post cycling performances in triathlons and report that this phenomenon commonly subsides within a few minutes (Vieten & Weich, 2020; Weich et al., 2019). This phase of finding-a-rhythm might be related to the well-known transient oscillations described in dynamical systems (Strogatz, 2015). Respecting scale invariance, numerous examples, such as analytical equations (Alligood et al., 2000), human neurology (Peterka & Loughlin, 2004), as well as biomechanics (Kaminski, Padua, & Blackburn, 2003), are characterized by this behavior. If any dynamical system is initiated or affected by an internal or external perturbation, it takes some time to even out to a balanced condition. The asymptotical equilibrium reached after these perturbations can be called an attractor (Precht, Voit, & Kraft, 2005; Van Hooren, Meijer, & McCrum, 2019). The crossed trajectories, i.e., the paths of the systems’ states over time, are called transients. Once initialized, these transients show rapidly changing and mostly irregular behavior over a short-lived period until settling down to the attractor (Precht et al., 2005). Based on these observations, human cyclic motions, such as walking or running, can be described as limit-cycle attractors (Broscheid et al., 2018; Kelso, Holt, Rubin, & Kugler, 1981; Vieten et al., 2013). An approach to analyze attractors, the attractor method, derived from human cyclic motion was introduced by Vieten et al.
The latter yields very sensitive results allowing the analysis of subtle changes of movement patterns and their variations. The application and further studies assessing athletes while undisturbed running and cycling indicated the existence of a transient effect at the onset of physical activities (Weich et al., 2019). Recently Vieten and Weich (2020) extended these earlier findings by demonstrating a mathematical model of the kinematics of human cyclic motion when considering transient oscillations a crucial component of locomotion. The starting value of the deflection is very subject-specific and influenced by randomness. Nevertheless, progress from the beginning of the run until finally levelling off can be modelled as the solution of a damped harmonic oscillator decreasing with a negative exponent as a function of time. Once a runner has reached this point, the transient effect remains, but its extent is reduced to a level that is subjectively no longer perceptible to the athlete (Vieten & Weich, 2020).

Based on the mathematical model, the aims of the present study were to determine the existence of the transient effect and to quantify it in athletes running at moderate speed. The analysis focused on the magnitude and duration of the movement's transient fluctuations and their subject-specific characteristics. It was also considered whether training level, athletic experience, or anthropometric preconditions were related to this phenomenon. Insights emerging from this research may provide new aspects concerning the nature of running, opening new possibilities for race pacing and overall performance.

### 3.3 Materials and Methods

A total of 30 athletes (Table 9), 10 female and 20 males, were tested from October 2019 until June 2020 in Kreuzlingen, Switzerland (Elitesportschule Thurgau). All participants were regularly physically active, and none were suffering any current injury, which would have impeded their performance. The only prerequisites were to be able to run for 60 min without reducing their expected performance which had been determined in advance. Furthermore, training level and experience, using the training hours per week and the number of years the athletes had been running, were obtained. The study was approved by the local Ethical Committee of the University of Konstanz, Germany, under the Ref. No: IRB20KN08-001. All participants were requested to fill out and sign an informed consent.
Table 9: Subject overview.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Age (y)</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
<th>Test speed (km/h)</th>
<th>Training (h/week)</th>
<th>Running Experience (y)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>10</td>
<td>29 ± 11.5</td>
<td>166 ± 5.5</td>
<td>55.7 ± 4.0</td>
<td>9.6 ± 1.4</td>
<td>3.6 ± 1.8</td>
<td>10.9 ± 8.3</td>
</tr>
<tr>
<td>Male</td>
<td>20</td>
<td>29 ± 11.1</td>
<td>180 ± 5.6</td>
<td>70.1 ± 6.7</td>
<td>11.5 ± 1.5</td>
<td>4.6 ± 2.2</td>
<td>10.7 ± 10.9</td>
</tr>
<tr>
<td>Overall</td>
<td>30</td>
<td>29 ± 11.3</td>
<td>175 ± 8.9</td>
<td>64.9 ± 9.1</td>
<td>10.8 ± 1.4</td>
<td>4.2 ± 2.1</td>
<td>10.8 ± 9.8</td>
</tr>
</tbody>
</table>

To collect the necessary raw accelerometer data, two inertial sensors were used (RehaWatch by Hasomed, Magdeburg, Germany). The sensors have a size of 60 × 35 × 15 mm and weigh 35 g each. They function as a triaxial accelerometer with up to 16 G, a triaxial gyroscope with up to 2000 °/s and a magnetometer measuring with 1.3 Gauss. The device is constructed as a micro-electro-mechanical-system (MEMS). For the current study, the MEMS measured the acceleration of the feet in three dimensions (x, y, z) with data saved to a smartphone (J5 by Samsung, Seoul, South Korea). To collect the running motion, the sensors were attached to both ankles above each lateral malleolus by a hook-and-loop fastener. The runs were performed on a treadmill (9500HR by Life Fitness, Unterschleißheim, Germany).

Each runner had to run two sessions at a constant speed over 60 min. Before they started the first test session, they were asked to self-select their running pace, defined by a subjective feeling associated with a BORG CR-10 scale value of 3 to 4, i.e., moderate to somewhat severe (Borg, 1998). Afterwards they were equipped with the two activated MEMS sensors attached to the ankles as described above. The treadmill was set at 1 % inclination, to simulate air resistance, and the individual running speed. Once the speed was reached the data collection was started right before the runner jumped smoothly from the lateral standing area of the treadmill to the actual moving belt (the jump was subsequently removed by cutting out the first 1.5 s of the data set). During the sessions the smartphone was placed beside the treadmill. The measurements were received at a sampling frequency of 500 Hz assembled over a period of 60 min without interruption.
Recently, Vieten and Weich (Vieten & Weich, 2020) introduced a model to mathematically describe the kinematics of human cyclic motion. Based on their model, six elements contribute to overall human cyclic motion. Here, the subject’s individual attractor $\hat{A}(t)$, a limit cycle in acceleration space, which is repeated in each cycle, is by far the biggest contributor. In addition, short-term fluctuations (random walk) around the morphed attractor, a control mechanism that regulates the latter if the current movement accelerations deviate too much from the attractor and technical (white) noise from the MEMS sensors contribute to the overall movement. These three components have an average contribution of zero due to cancellation processes and thus can be neglected in the context of this publication. Furthermore, the kinematics are markedly more affected by so-called attractor morphing $\vec{M}(t)$, a process which slowly changes the actual attractor and transient oscillations $\vec{T}(t)$. To reveal the morphing process $\vec{M}(t)$ and the transient oscillations $\vec{T}(t)$, the attractor must be subtracted from the measured signal $\vec{K}(t)$.

$$\vec{K}(t) - \hat{A}(t) = \vec{M}(t) + \vec{T}(t) \quad (16)$$

These two terms, morphing and transient effect, are retained, when the reduced attractor is developed. So, the transient effect’s contribution can be written as

$$\vec{T}(t) = \vec{K}(t) - \hat{A}(t) - \vec{M}(t) \quad (17)$$

Morphing $\vec{M}(t)$ contributes minor changes to the attractor over the time of the activity. Thus, the effect is generally bigger between different runs as compared to changes within a run. Because the transient effect decreases asymptotically within the first minutes, a super attractor $\hat{S}$ is created as the mean of all one-minute attractors of a single running session. This results in the closest approximation to the second and third terms of the right-hand side of equation (17)

$$\hat{S} = \langle \hat{A}(t) - \vec{M}(t) \rangle \quad (18)$$

and following the transient effect can be approximated by

$$\vec{T}(t) = \vec{K}(t) - \hat{S} \quad (19)$$

which allows the calculation of the transient time from

$$\frac{T(t_{\text{trans}})}{T(t = 0)} = e^{-1} \quad (20)$$
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Since further analysis was required, the collected 60-min data block was divided into 60 s intervals using a file splitter to produce 60 single datasets. Afterwards the MATLAB app Attractor was used to calculate the attractor data of each one-minute data set. The functionality of the Attractor app is based on the Attractor Method developed by Vieten and colleagues (Vieten et al., 2013) and is available online via http://www.uni-konstanz.de/FuF/SportWiss/vieten/CyclicMove/. Further, a super attractor $\mathcal{S}$ of each run was calculated to represent each participant’s individual gait-print as a mean attractor of all single minutes of each session (Weich & Vieten, 2020).

To detect, quantify, and validate the transient effect of a running performance, three mathematical procedures were considered (Figure 9):

![Figure 9: Outcome (subject 26, session 1) for the transient values from all three calculation methods: $\delta M$ in red, FFT in blue and FFTmod in green. The transient effect can clearly be seen at the onset of the run. The data from FFT and FFTmod were normalized to the data from $\delta M$ to improve the visualization of the comparison. This had no influence on the result.](image)

Figure 9: Outcome (subject 26, session 1) for the transient values from all three calculation methods: $\delta M$ in red, FFT in blue and FFTmod in green. The transient effect can clearly be seen at the onset of the run. The data from FFT and FFTmod were normalized to the data from $\delta M$ to improve the visualization of the comparison. This had no influence on the result.
Delta M ($\delta M$, method I)

The parameter $\delta M$ represents the velocity ($v$) normalized average distance between two attractors and can be described as follows (Vieten & Weich, 2020)

$$
\delta M = \frac{1}{v} \left( T_{||} \cdot \left[ e^{\frac{-t}{t_{\parallel}}} - e^{\frac{-t}{t_{T}}} \right] + a_0 \cdot \left\{ \left( \frac{t_{E} - t}{t_{E}} \right) + a_1 \cdot \sin \left( a_2 \cdot 2\pi \left( \frac{t_{E} - t}{t_{E}} \right) \right) \right\} \right)
$$

(21)

where the given constants $T_{||}, t_{T}, a_0, a_1, a_2$ are derived from a curve fitting application of all measurements (CurveExpert Professional 2.6.5, version 2.6.5, Hyams Development), using the Levenberg–Marquardt algorithm.

The constants $a_0, a_1, a_2$ represent the morphing process whereas $T_{||}$ and $t_{T}$ are based on the transient oscillations at the onset of a movement (Vieten & Weich, 2020). $t_{T}$ quantifies the time until the oscillation decreases to $e^{-1}$ of its original starting value $T$.

The super attractor $\vec{S}$ of each running session was taken as a stable condition to be compared to each single minute from the start of the exercise bout until the end of minute 60. Since the super attractor, by definition, represents only one cycle and the Attractor app can only compute multiple cycles in one data set, each one was extended to a data set with a total duration of one minute. For this data set, which is designated as a super minute, the original cycle is repeated according to the average cycle length.

The starting value of the oscillation is highly dependent on the individual and is further affected by random processes. The average distance between two attractors, defined as $\delta M$, for the same subject, is small, compared to attractor differences between different subjects (Weich & Vieten, 2020).

Accordingly, the result of this analysis provides a $\delta M$ value for each comparison between one of the single minutes and the super minute, so that a list of sixty $\delta M$ values in temporal sequence describes the transient process over the entire session (Figure 9, red curve). A smaller $\delta M$ number means a higher similarity of the compared attractor pairs. The latter procedure is executed using the Attractor app comparing the super attractor $\vec{S}$ (in the super minute version) with the measured acceleration data leading to the transient time $T(t)$ when further processed with the curve fitting software (CurveExpert Professional 2.6.5, version 2.6.5, Hyams Development).
Fast Fourier Analysis (FFT, method II)

The Fast Fourier Analysis (FFT) (Winter, 2005) was used as a second possibility to quantify the transient effect (Figure 9, blue curve). This enables the recorded data to be viewed in the frequency domain to allow the possibility of filtering to maintain only the essential data choosing a suitable cutoff of 10 Hz. In both, frequency and time space, the $L^2$ norm is used. Based on the Plancherel theorem (Iosevich & Liflyand, 2014), which states that for $L^2$ functions the norm of the time domain is retained in the FFT (frequency domain), the transient time can be described as below:

$$\int_{-\infty}^{+\infty} |g(t)|^2 dt = \int_{-\infty}^{+\infty} |F(f)|^2 df$$ (22)

This allows the calculation of the transient effect using the Fourier transform of the reduced signal as a measure of the discrepancy of the measured running minutes $\tilde{K}(t)$ from the super attractor $\tilde{S}$, which represents the athlete’s average running behavior. The calculation of a scalar is independent of the used coordinate system. It follows:

$$T(t) = \sqrt{\int_0^{t_e} (\tilde{K}(t) - \tilde{S})^2 dt} = \sqrt{\int_{-f_c}^{f_c} F^2(f) df}$$ (23)

where $f_c$ is the cut off frequency (here 10 Hz), because the information content of a filtered signal is considered and $t_e$ representing the final minute of a running session. The transient effect is treated as a damped harmonic oscillator (Vieten & Weich, 2020). As a temporary oscillation around the attractor, these oscillations have contributions corresponding to the harmonics up to the cut off frequency only. All other contributions mentioned above, those of the frequencies different from the harmonics, naturally cancel out due to destructive interference. Thus, the numerical calculation of the right-hand side of Equation (22), is executed as adding up all amplitudes of the harmonics up to the cut off frequency which was set at 10 Hz.

$$T(t) \sim \sqrt{\sum_{i=1}^{n(f_c)} F^2(f_i)} = CoH(t)$$ (24)

The expression ($CoH(t)$: collection of harmonic amplitudes) is proportional to the transient contribution and is impacted very little by other contributions to movement. The attractor and morphing, which change rather slowly ($\ll 1$ Hz), were subtracted
before the Fourier transform. Furthermore, the residuals do not contribute very much because their contribution is almost always different from the harmonics. The contributions of the other movement parts (noise, short-term fluctuations and the control mechanism) have contributions that differ from the harmonics and thus are not subtracted. As a consequence, the Fourier transformed expression allows for a more accurate calculation of the transient time, $t_{trans}$, using curve fitting software (CurveExpertPro, version 2.6.5, Hyams Development).

\[
\frac{\text{CoH}(t_{\text{trans}})}{\text{CoH}(t = 0)} = e^{-1} \tag{25}
\]

**Modified Fast Fourier Analysis (FFTmod, method III)**

Another, third, way of calculating $T(t)$ can be carried out as follows:

\[
T(t) \approx \sqrt{\sum_{i=1}^{n(f_c)} F_{K^2}(f_i) - 2 \sum_{i=1}^{n(f_c)} F_{KS}(f_i) + \sum_{i=1}^{n(f_c)} F_{S^2}(f_i)} = \text{CoHmod}(t) \tag{27}
\]

Where (CoHmod(t)) collection of harmonic amplitudes from the FFTmod method) is proportional to the transient contribution and is not impacted by the other contributions.
of the movement. Again, the Fourier transformed expression allows for a more accurate calculation of the transient time, $t_{\text{trans}}$, using curve fitting software. Therefore equation 25 can be used applying harmonic amplitudes resulting from the FFTmod calculations.

It was still expected that the transient times of both FFT methods would be very close together. For this reason, a correlation was also calculated for this relationship. When calculating the transient time $T(t)$ using method I, the transient effect and the residuals of the described components of human cyclic motion (morphing, short-time fluctuations, control mechanism, noise) (Vieten & Weich, 2020) are included. The Fourier transform, on the other hand, allows the two other applications (II and III) to isolate the transient effect, because the latter is found mainly in the harmonics. Thus, an intraclass correlation (executed with SPSS version 26.0) was used to calculate the strength between method I and II/III. This statistical method provides a measure of the proportion of variance that is attributable to the objects being measured. Consequently, to be able to make a decision about the presence of the transient effect, method one (I) and at least one of the two FFT methods (II or III) must be computed. A high ICC implies that most of the variance is among group/method. If the test reveals a high intraclass coefficient (ICC), $r$ means that the checked running data show a substantial transient effect (Figure 10, black data). A low ICC (Figure 10, red data) would rather reflect the absence of initial oscillations. In order to be able to determine the strength of the resulting ICC, the categorization according to Hopkins (2000) was used. Hopkins expands on the original work of Cohen (1988) by further classifying coefficients greater than 0.5 (strong) into very high ($r = 0.7−0.9$) and almost perfect or indistinguishable ($r > 0.9$). For the present work, an $r > 0.7$ is regarded as a suitable magnitude to assume the existence of a substantial transient effect. Furthermore, this corresponds to a coefficient of determination ($R^2$) above 0.49, which explains at least 49 % of the variance.
In a final step the collected anthropometric and performance data were statistically analyzed via correlation (executed with SPSS version 26.0) to determine whether running experience is related to the observed transient times.

3.4 Results

Of the 60 sessions (two for each subject), 48 (for FFT) and 49 (for the FFTmod) cases showed a transient behavior at the onset of the running session (Figure 11). This corresponds to 80 and 81 % of the cases considered, respectively. It can be observed that for FFT in two and for FFTmod in one case, both runs of a person showed no transient effect (subject 27 for both methods, and also 13 for FFT). Another eight participants (2, 3, 6, 9, 16, 21, 25, 28) had a mixed result (for FFT and FFTmod) and showed one run with and one without a transient effect. Only one person (13) offered a mixed result for FFTmod but displayed no transient effect for both runs using the FFT. In general, the correlation (ICC) between the FFT methods was calculated with a mean $r = 0.99$, indicating a high accordance of both approaches.
Figure 11: Overview of the transient effect for all subjects across the two sessions listed for example as: 1 = subject 1 session 1; while 1_2 = subject 1 session 2. White bars with a frame represent the ICC of the FFT method and the filled black bars the FFTmod method. The white horizontal line displays the critical r of 0.7. Correlations reaching above the white horizontal bar were considered to have a detectable transient effect.

Furthermore, the extent or duration of the transient effect was calculated for those runs that displayed a transient effect (48 cases for FFT and 49 for FFTmod). On average, the initial transient oscillations, i.e., the time it takes athletes to find their rhythm, took 4.99 (±3.35) minutes when the data were evaluated with the FFT method, and slightly longer, 5.50 (±4.72) minutes using the FFTmod method (Figure 12). The transient effect ranged from 31 min (subject 8) on the higher end to less than one minute (subject 17, run 1; subject 20, run 2) for the shortest.
Figure 12: Overview of the transient effect for all subjects across the two sessions listed, for example, as: 1 = subject 1 session 1; while 1_2 = subject 1 session 2. White bars with a frame represent the transient time in minutes calculated by the FFT method and the filled black bars the time derived by the FFTmod method. All cases without detectable transient oscillations at the onset of their run were excluded.

To determine whether anthropometric or performance characteristics were related to the transient time, only runs that showed a transient effect (according to the above explained analysis methods) were considered. As Table 10 shows, none of the recorded anthropometric or performance measures were significantly correlated to transient time ($p > 0.05$).
### 3.5 Discussion

The main objective of the present study was the detection and quantification of the transient effect in human running. It was shown, that depending on the analysis method, this effect occurred in 80−81 % of the running sessions in the participating subjects. The average time until an athlete found a running rhythm was 4.99 (FFT) to 5.50 (FFTmod) minutes, with the longest adaptation time being 31 min. Furthermore, the results of the FFTmod (Equation (27)) can be classified as clearer, since the Fourier Transform separates the morphing and other components of cyclic human motion from the transient effect before combining the parts of the mathematical equation. Both the occurrence and the duration of the transient effect were independent of body characteristics and performance measures such as running level, weekly training hours, and training age (all p > 0.05).

The high appearance of the transient effect in more than 80 % of the recorded runs suggests that the transient effect is a quite common phenomenon within the context of the participating group, the performance level, and a moderate running pace. The current participants may be expected to be representative of the general running community, as they represent a high range of age (18 y–55 y), training experience (1 y–40 y), running performance expressed as the pace for a moderate endurance run (8 km/h–15 km/h) and weekly training hours (0.75 h–10.5 h). This is further supported by the fact that none of the mentioned specific performance or body data are significantly related to the occurrence of the transient effect.

The duration of the transient effect is defined as the time required to reduce the magnitude of the initial state of the transient value (Figure 9, first data point of the curves) to e⁻¹. The average time derived from the data of this study was 5.25 min,
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which is consistent with reported observations of experienced runners. In addition to these observations, there is also a scientific data base that describes a similar time frame for changes in running rhythm in related contexts like the transitioning from cycling to running in triathlon (Gohlitz et al., 1994) or from walking to running and back (Diedrich & Warren, 1995; Segers et al., 2006). As an example, Gohlitz et al. (1994) reported differences in adaption time of the prior working muscular conditions in cycling and running. Their main finding was that immediately after the transition the athlete’s body takes a while to adapt to the varying motion. During this phase, lasting around 1200 m, the stride frequency decreased, and the stride length increased until the participants regained their personal optimum (measured earlier in another 5000 m run). This adjustment was also consistent with their subjective feeling during the run. Witt (1994) confirmed these results and tried to interpret them with physiological and biomechanical explanations after testing triathletes during a run-cycle-run condition. The author claimed that cycling destroyed the activity pattern of a subsequent run due to extremely different working conditions of the muscles between both disciplines. Later, Weich et al. (2019) published a cross-over study with triathletes based on this idea and compared isolated running over 5 km with a run of the same length after prior cycling. In this context, they noted that there was not only, as expected, a transition phase when running after preload, but also during the solo run. The average duration mentioned in this paper was 7 min for both types of running. Here, too, the authors proposed predominantly neuromuscular reasons for the initial transient effect. It should certainly remain a major objective in future studies to show the exact origin of these phenomenon.

Even though the vast majority of the runs in the current study showed a transient effect, there are also participants who either had no initial oscillations or a mixed outcome with one run showing an effect whereas the other had none. This has also been shown in previous studies (Vieten & Weich, 2020; Weich & Vieten, 2020). Vieten and Weich reported, that the starting value of the deflection is very subject-specific and influenced by randomness. It can therefore be assumed that, especially in the case of a mixed result for one person, the athlete found his or her rhythm by chance and was close to his or her individual attractor right from the beginning. Thus, the athlete did not undergo a prominent transient effect, which, as a consequence, was not visible. Further a subject-inherent property in the motor control system could be responsible. Systematic (or nonsystematic) fluctuations over the entire run have the same magnitude as the
transient effect, so that it does not appear prominently (see Figure 13 for subject 9, session 1). In this case, it could be because the subject has, with only 1.5 years and 2.5 weekly training hours relatively little running experience. In simple terms, this athlete repeatedly experiences deviations from his/her running rhythm, which he/she has to gain back over and over again. One could almost say that these fluctuations are multiple small transient effects, which the subject has to overcome. The cause for these fluctuations may also lie in other components of cyclic human motion, e.g., morphing as well as the residuals of short-time fluctuations, control mechanism and noise. They can be so pronounced that they obscure the transient process. A further scenario can be seen in athlete 13, who is almost a professional runner experiencing no transient effect in any of the runs. Here the assumption is quite reasonable that he/she is able to find the running rhythm very rapidly due to the high level of performance and many thousands of kilometers of yearly running (more than 100 km per week). However, to confirm this assumption, a separate study with multiple professional runners at the same or even better level is needed. In general, if the initial numerical value of a session is already very low (as in Figure 13, only 1.5), this means that the data is very similar to the general trend (represented by the super attractor). Thus, it is very likely that the transient effect will not be visible.

Figure 13: Outcome (subject 9, session 1) for the transient values calculated by δM in red, FFT in blue and FFTmod in green. In this example, there is no transient effect, since it is probably overlaid by strong fluctuations of the same magnitude over the entire run (r = 0.6). The y-axis scale was adapted to Figure 9 to highlight the difference between the starting values. The low numerical transient value of 1.5 here indicates that most probably no transient effect will be detected. The data from FFT and FFTmod was normalized to the data from δM to clarify the visualization of the comparison. This had no influence on the result.
On the other hand, it sometimes happened that there were slight disturbances (e.g., a short stumble) during a session, but these were smaller than the transient effect and so short that the running behavior was not affected. If the athlete is impaired by minor, short-term disturbances (Figure 14, for example minute 17, marked with the black arrow), the presented analysis method seems to be robust to the extent that the system balances out again within a short time period. In a practical sense, the question arises as to what influence the transient effect at the beginning of a training session or competition has on running performance. To be able to clarify this question with certainty, it is necessary to examine metabolic or physiological data, such as oxygen uptake, heart rate, electromyography etc., which would provide further insights into the course of events happening during the initial phase of the exercise. From this study, anecdotal evidence suggests that running (without warm-up) was perceived as more comfortable after a few minutes into the run. If the transient effect should have a negative impact on running performance, this could be another powerful argument for an extended warm-up before each training session or running competition (Bishop, 2003; Friel & Vance, 2013). This would allow the athlete to be in his or her individual running rhythm at the start of the race or the main part of the training.

Figure 14: Outcome (subject 22, session 1) for the transient values calculated by FFT in blue and FFTmod in green. In this example, the data show a transient effect (transient time = 4.23 min (FFT) and 4.3 (FFTmod); r > 0.9), although the course of the session shows minor disturbances (like minute 17 (black arrow), which were controlled within a short time period. The y-axis scale was adapted from Figure 9 to highlight the difference between the starting values. The data from FFT and FFTmod was normalized to the data from $\delta M$ (not shown) to improve the visualization of the comparison but had no influence on the result.
In order to strengthen the general validity of this phenomenon, future studies should validate the outcome of the test procedure in an outdoor setting and at varying or self-selected running speeds. Furthermore, the analysis in this study was carried out only with experienced nonprofessional runners. It remains open how the transient effect behaves in novice or professional runners. It could also be interesting to include other cyclic sports such as swimming, cycling, walking or rowing.

3.6 Conclusions

In summary, it can be concluded that by applying the attractor method and the described analysis process of the data in frequency space, a transient effect can be detected in over 80 % of the recorded running sessions. On average, the initial oscillations lasted 5.25 min, which correspond to about 500–1000 m, depending on running ability. This also corresponds to the subjective feeling that athletes report empirically. For the runners who did not experience a transient effect, other components of their running kinematics, such as morphing, might have hidden the phenomenon. Because the FFTmod method contains predominantly fractions of the transient effect, it produces the most precise outcome and is therefore the recommended method. Taking into consideration further physiological and metabolic data in future works will offer the chance to determine the influence of this phenomenon on athletic performance in training and competition.
**Funding:** AFF-grant “cyclic human motion—2019” of the University of Konstanz. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

**Acknowledgments:** We thank all subjects who participated in the study.

**Conflicts of Interest:** The authors have declared that no competing interests exist.

**Ethic Statement:** The study was approved by the local Ethical Committee of the University of Konstanz, Germany under the Ref. No: IRB20KN008-01.

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4 STUDY 3: The Gaitprint: Identifying Individuals by Their Running Style

SENSORS

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Bibliographic reference:
The Gaitprint: Identifying Individuals by Their Running Style

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Received: 3 June 2020; Accepted: 6 July 2020; Published: date

4.1 Abstract

Recognizing the characteristics of a well-developed running style is a central issue in athletic sub-disciplines. The development of portable micro-electro-mechanical-system (MEMS) sensors within the last decades has made it possible to accurately quantify movements. This paper introduces an analysis method, based on limit-cycle attractors, to identify subjects by their specific running style. The movement data of 30 athletes were collected over 20 min. in three running sessions to create an individual gaitprint. A recognition algorithm was applied to identify each single individual as compared to other participants. The analyses resulted in a detection rate of 99 % with a false identification probability of 0.28 %, which demonstrates a very sensitive method for the recognition of athletes based solely on their running style. Further, it can be seen that these differentiations can be described as individual modifications of a general running pattern inherent in all participants. These findings open new perspectives for the assessment of running style, motion in general, and a person’s identification, in, for example, the growing e-sports movement.

Keywords

attractor method; human cyclic motion; running quality; individual locomotion; recognition
4.2 Introduction

Quantitatively describing and understanding the characteristics of a well-developed and efficient running style is a central issue in athletic sub-disciplines. It is not without reason that running efficiency is considered to be one of the three determinants of endurance performance alongside aerobic capacity (VO$_{2\text{max}}$) and the fractional utilization of the VO$_{2\text{max}}$ (Bassett & Howley, 2000; Magness, 2014). The identification of subject-specific running characteristics is crucial for approximating towards a better understanding of running efficiency from a biomechanical standpoint. Since the early seventies, experimental psychology has demonstrated high identification rates of so-called bio-motion animations (Troje, Westhoff, & Lavrov, 2005). Here, viewers were able to recognize gender, body physique, tension, and even the mood of a walking person simply by watching white dots on a black screen representing their major joints. While subjective observation data (Cutting & Kozlowski, 1977; Johansson, 1973), the understanding and interpretation of human motion recognition, is certainly not a new endeavor, smart surveillance, robotics, medical applications and others, as well sports and exercise have taken advantage of the growing technology and methods (Kale & Patil, 2016, Table 1) within the last two decades. Especially, the analyses of athletic movements and postures may potentially improve the athlete’s competitiveness and reduce the injury risk. Furthermore, within the last decade, with the field of e-sports another interesting area of application has emerged. Since 2006, when Nintendo released its Wii console, motion-controlled gaming systems have evolved so much that they are now used for therapeutic (Bower et al., 2015) and educational purposes (Jenny, Schary, Noble, & Hamill, 2017). Today, there are two application methods when dealing with human motion recognition: the vision- or video-based approach and the use of wearable sensor technology worn by the user. Before the latter was introduced to the mass market in the past decade, earlier work, like that by Schoellhorn, Nigg, Stefanyshyn and Liu (2002), relied on force plates and mainly video data as an effective tool to identify locomotion characteristics. In the late nineties, (Aggarwal & Cai, 1999) provided a concise article about what was possible in terms of human motion analysis at that time. The recognition of persons or activities on the basis of body parts was seen as fundamental, mostly in comparison with pre-defined models (Troje et al., 2005) without separating into body parts, but rather focusing on the person or activities as a whole based on consecutive image sequences. Later, they revised their earlier work,
which concentrated on simple actions, and expanded it with methodologies dealing with human actions, interactions and group activities (Aggarwal & Ryoo, 2011). Until the end of the 2010s, studies on the recognition of persons based on their gait were largely based on these technical circumstances. For example, Goffredo, Bouchrika, Carter and Nixon (2010) presented for the first time, a methodology in which video sequences with widely different walking persons achieved a recognition rate of 92.2%. The recognition was marker-free and without prior calibration of the cameras. In 2011, Lin, Yang, Lin & Yang (2011) focused in their work on kinematic and kinetic parameters of the lower limb joints. The group combined a marker-based motion capture system with force plates with a self-organizing neural network map on the software side. Their biometric methodology, which did not use a marker-free approach for reasons of precision, achieved a very high recognition rate of 99.07% on average for all examined joints (hip, knee, ankle).

In contrast to these traditional raw data, as well as data from optical motion capture or magnetic tracking systems, modern research rather draws upon inertial sensors collecting acceleration and gyrometer data. The latter devices are constructed as a micro-electro-mechanical-system (MEMS) and are useful due to with their size, weight, cost-efficiency, and low power consumption (Espinosa et al., 2015; Gouwanda & Senanayake, 2008). They have also been shown to be convenient and easy-to-use in different practical sport settings and rehabilitation related contexts (LEOMO Inc., 2017; Yang & Hsu, 2010). A recent study (Zhao & Chen, 2020) in the sport of basketball focused on the use of MEMS sensors to detect complex, sports-typical movements of the upper extremities, such as dribbling, catching, passing, and throwing. The group used well-known computer-based evaluation methods (Principal component analysis and support vector machine) and presented a highly reliable method with an average recognition rate of 96%.

MEMS sensors collect joint coordinate tracks, which can be compressed into an entity called an attractor. An individual attractor can be regarded as a mean cycle derived from multiple gait or running cycles during a session, lasting from seconds up to several minutes (Vieten et al., 2013). Based on the latter, current works in sports rehabilitation propose a highly individual foot acceleration print (Byrnes et al., 2018) or gaitprint (Broscheid et al., 2018) representing a unique characteristic of a person’s gait. They can be understood as an analogue to a fingerprint, representing a singular pattern of a human finger, which will only match with one particular person. Assigning a gaitprint
to single individuals would open the possibility to identify people based only on their stride characteristics.

The Attractor Method (Vieten et al., 2013) uses acceleration and gyrometer raw data derived from MEMS sensors to produce sensitive results allowing for the objective analysis of subtle attributes in movement patterns and its variation. Vieten et al. (2013) and Broscheid et al. (2018) reported that human cyclic motions, such as running or cycling, can be described as limit-cycle attractors and thus be used to create individual gaitprints from whole movement sequences. Individual attractors, created by a computer algorithm, representing the full motion cycle data of the moving subject, can be stored in a database for further analysis. Once a new short running sequence is recorded, at a later time it can be compared with the database to screen out the dataset with the highest concordance. In a theoretical paper, Vieten and Weich (2020) demonstrated that this process enabled discrimination between an individual’s and other persons’ running patterns. Moreover, the authors described extra components of human cyclic motion—attractor morphing, short time fluctuations, transient effect, control mechanism, and technical noise—adding further variation to the individual limit-cycle attractor, which must be taken into account during the recognition process (Vieten & Weich, 2020).

The aim of the current study was to establish that athletes can be recognized by their running style. It is shown that an algorithm, which is based on the Attractor Method, is capable of recognizing a running person based solely on data received from MEMS sensors. The present study demonstrates that the detection rate is as high as 99 %, while the false identification probability is 0.28 % overall. From this, it can be concluded that running style is highly individual. Beyond the recognition capability, the Attractor Method approach further aimed to highlight the kinematics of this procedure and to pave the way for a better understanding concerning running quality in athletic contexts.

### 4.3 Materials and Methods

A total of 30 athletes (Table 11), 9 females and 21 males, were tested from April till July 2018 in Kreuzlingen, Switzerland (Nationale Elitesportschule Thurgau). All of the participants were active and experienced runners, none did show any present injury signs at this point, which could have possibly impeded their performance. The only prerequisites were to be aged 18 years or older and able to run 20 min. without reducing the pace, which had been determined in advance by a lactate threshold test. 
The participants started with a speed of 8 km/h, which was increased every 3rd minute by 0.5 km/h separated by 30 s pause to take a lactate sample until exhaustion. The study was approved by the local Ethical Committee of the University of Konstanz, Germany, under the RefNo: IRB20KN10-009. All of the participants filled out and signed an informed consent.

Table 11: Subject Overview.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Age (yr)</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
<th>v_{run} (km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>9</td>
<td>29 ± 5.2</td>
<td>169 ± 5.2</td>
<td>59.9 ± 5.6</td>
<td>12.4 ± 0.9</td>
</tr>
<tr>
<td>Male</td>
<td>21</td>
<td>36.8 ± 11.9</td>
<td>179 ± 6.4</td>
<td>73.9 ± 6.8</td>
<td>13.9 ± 1.4</td>
</tr>
<tr>
<td>Overall</td>
<td>30</td>
<td>34.7 ± 11.4</td>
<td>176 ± 7.6</td>
<td>69.7 ± 9.1</td>
<td>13.4 ± 1.5</td>
</tr>
</tbody>
</table>

To collect the necessary raw accelerometer data, two inertial sensors were used (RehaWatch by Hasomed, Magdeburg, Germany), which were attached to both ankles by a hook-and-loop fastener. The latter assured a stable fixation right above both lateral malleoli, which guaranteed the sensor positioning to be identical in all trials. The sensors have a size of 60 × 35x15 mm and weigh 35 g each. They function as triaxial accelerometers with up to 16 g (1 g = 9.81 m/s²), triaxial gyroscopes with up to 2000°/s and a magnetometer, which data that were not used within this study. The sampling rate was consistently set at 500 Hz. The acceleration data were gathered while using the app RehaGait Version 1.3.9 of Hasomed (Magdeburg, Germany) with data saved to a smartphone (Samsung Galaxy J5, Seoul, South Korea). The recordings of the feet were collected in three dimensions (x, y, z) in the coordinate system co-rotating with the legs. The hardware to measure the lactate content of the blood was a Lactate Scout and proper lactate sticks (by Senslab GmbH, Leipzig, Germany). The software Ergonizer (by Prof. Dr. Kai Röcker, Freiburg, Germany) was used to compute the individual anaerobic threshold.

The participating athletes repeated the testing protocol in a timeframe of approximately two weeks consisting of four testing days separated by at least 24 h. On the initial test day, they performed a lactate step-test (LT) to determine their individual anaerobic threshold. Further tests on days two to four (run 1–3 decoded R1–3 for further use) consisted of 20 min. of running on a treadmill. The speed for all sessions was set to a running pace according to 95 % of the lactate threshold speed. During all tests, the
participants were equipped with two activated acceleration sensors, as described
above, attached to the ankles atop each lateral malleolus. The smartphone to collect
the data was placed on a desk beside the treadmill to ensure undisturbed reception.
Further analysis required the collected 20-min. data block to be divided into 60 s
intervals. A file splitter was applied to produce 20 single datasets. The raw data text-
file contained thirteen columns: time and the acceleration as well as the gyroscope
data in x, y, and z directions for the left and the right foot, respectively. Afterwards, the
Attractor App was used to calculate the attractor data of each one-minute data set. The
functionality of the Attractor App is based on the attractor method developed by
(Vieten et al., 2013) and that uses acceleration and gyroscope data to produce
sensitive results allowing the objective analysis of subtle attributes in movement
patterns and its variation. The app is available online via http://www.uni-
konstanz.de/FuF/SportWiss/vieten/CyclicMove/. Furthermore, one of the running data
sets of each subject (only minutes 11 to 20 of R1, R2, or R3) was taken to calculate a
mean attractor, named super attractor, representing the individual running pattern. In
the calculation data from the left and the right foot were taken to establish the super
attractors of both feet. The advantage of the super attractor, a mean of 10 attractors of
one running session, in contrast to a comparison with a single minute, is the avoidance
of outlier or extreme attractors. For the latter, calculation only of minutes 11–20 were
included, to ensure that the athletes had already left their transient phase (Vieten &
Weich, 2020). All of the datasets were speed-normalized according to their individual
running pace to be comparable. Additionally, to prepare for the recognition analysis, a
recognition horizon around each single attractor point, was calculated. This horizon
was defined as the volume area at a distance equal to five standard deviations around
each attractor point. The choice of the data set (R1–R3) chosen for calculating the
super attractor was balanced over the three trials. This compensated the influence of
a possible bias, such as the learning effect. By creating 30 super attractors (due to 30
subjects) with their associated horizon, a catalogue was generated to undertake the
identification analysis. All other runs, two of each subject, constituted a comparison
pool.

To identify a person based on the running motion, any dataset, independent of the data
contributing to the respective super attractors and containing at least 50–60 cycles,
could be taken from any session. The algorithm was applied to all super attractors from
the catalogue using a point to point analysis to compare a newly chosen dataset to the
super attractor (Figure 15). The outcome of each tested comparison was a similarity rate, which was defined as the percentage of data points lying within the recognition horizon.

![Figure 15: Two-dimensional depiction of the three-dimensional recognition horizon (red) compared to an attractor of the same (subject A, blue) and a different subject (B, green).](image)

In this identification process all one-minute running sequences were compared with all super attractors in the catalogue. Altogether, 18,000 similarity rates (30 subjects x 2 runs x 10 sequences when compared to the 30 right and left side super attractors) were calculated. The comparison of a super attractor with attractors of the last 10 min. of a run, being runs as compared of one single individual or runs of a different individual, constitute a random event. As such, from a theoretical standpoint, the results are distributed normally with a definite mean and standard deviation. In addition, normality was numerically tested. With this, the probability of not identifying a subject can be set, in our case as $\alpha = 0.01$. The border discrimination between different and same persons’ similarity rate can then be calculated with the help of equation (28).
\[ \alpha = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi} \cdot \sigma_s} \cdot e^{-\frac{(x-\mu_s)^2}{2\sigma_s^2}} \, dx = \text{erf} \left( \frac{T - \mu_s}{\sqrt{2} \cdot \sigma_s} \right) \]  

This results in

\[ T = \mu_s + \sqrt{2} \frac{1}{\alpha} \]  

Finally, the probability of a false identification can be calculated while using equation (30).

\[ p = \int_{T}^{\infty} \frac{1}{\sqrt{2\pi} \cdot \sigma_d} \cdot e^{-\frac{(x-\mu_d)^2}{2\sigma_d^2}} \, dx = 1 - \text{erf} \left( \frac{T - \mu_d}{\sqrt{2} \cdot \sigma_d} \right) \]  

Here, \( \text{erf}(...) \) is the error function and \( \text{erf}^{-1}(...) \) the inverse. \( x \) represents the similarity rate, \( \mu \) and \( \sigma \), respectively, the mean and standard deviation of the probability density that describes the similarity rate of same subjects with the index \( s \) and for different subjects with the index \( d \). A graphic illustration of the relationships is provided in Figure 16.

![Figure 16: Example for two normally distributed probability curves (orange = between subject comparison; blue = within subject comparison; thin and thick dashed lines in orange and blue symbolize mean (\( \mu \)) and standard deviation (\( \delta \)); \( T \) is the border for rating different (left of \( T \)) and same (right of \( T \); \( \alpha \)-area = probability of not identifying a subject; \( p \)-area = probability of a false positive identification)](image-url)
Based on this general outcome, in the second step, the identification process was repeated for all super attractors to be compared only with the “worst-case data set”, meaning the subject who had the highest false recognition rate. We identified the similarity rates to be normally distributed (Kolmogorov–Smirnov statistic with \( p > 0.05 \)) and calculated the means and standard deviations using equations (28) to (30).

Recognition of a subject depends on the complete motion description, including all the kinematics. The methodology of (Vieten & Weich, 2020) was used to determine the influencing factors and the magnitude of attractor variations.

They describe the kinematics of human motion as a superposition of six contributing terms:

1. Limit-cycle-attractor, a closed line in acceleration space, representing the characteristic main contribution, which repeats in each cycle.
2. Attractor morphing, a slow deviation, deforming the actual attractor within well definable borders.
3. The transient effect occurring as temporary oscillations at the onset of a cycling movement, of which the strength decreases rapidly as a negative exponential function depending on time. Such initial transient oscillations can generally be found in many dynamical systems, like human neurology (Peterka & Loughlin, 2004) or biomechanics of muscles (Kaminski et al., 2003).
4. Short-time fluctuations in the form of a “random walk” around a morphed attractor.
5. The controlling mechanism, which kicks in when current accelerations deviate too much from the morphed attractor.
6. MEMS sensors’ noise

The latter is treated as white noise cancelling out over the course of time (mean = 0). A similar cancellation counts for the controlling mechanism in combination with the short-time fluctuations. These two effects together have a mean contribution of zero due to the random positive and negative contributions in three dimensions.

Super attractors were used to be compared with independent measurements of the single subjects to identify the magnitude of the individual attractor morphing. The outcome is a parameter termed \( \delta M \), as described in a paper introducing the attractor method (Vieten et al., 2013, p. 3) \( \delta M \) expresses the velocity normalized difference between two attractors, containing information about changes in the individual running
pattern. In general, the smaller $\delta M$ is, the more similar are the two compared attractors. Thus, it serves as an indicator for the magnitude of the morphing process. Further, Vieten and Weich (2020) reported that each continuous run is potentially accompanied by an initial transient phase lasting approximately 4 to 10 min. Based on this assumption, all of the running data included in the analysis of the gaitprint procedure only contained data that were collected after the initial ten minutes to exclude the impact of the transient effect.
4.4 Results

The similarity Procedure

The similarity procedure created a distribution of similarity rates presenting the same subject comparisons (green dots for run 1 and black x for run 2) and comparisons of subjects’ super attractor with the worst case run of a different person (gray bars) (Figure 17 a and b). For almost all cases, there is a distinct gap visible between the same- and the different subject comparisons. A sign that the recognition of a person is achievable with high probability.

![Figure 17: Recognition percentages presenting same-subject values (green dots in (a) & black crosses (b)) and different-subject (worst-case) values (grey dashes in (a,b)).](image-url)
The outcomes based on equation (30) concerning the probability of detecting a false positive assignment, when checking for an individual running pattern, are, on average, below 1% with a maximal false detection rate of approximately 9% (subject 11). Figure 18 shows a complete overview of all participants.

**Figure 18:** False positive detection probability chart displaying the individual percentages of all subjects. Squares = Super attractor versus the first run of the same person and filled triangles = Super attractor versus the second run of the same person. When probability is zero, squares are partly hidden by filled triangles.

**Morphing and Transient Analyses**

In addition to the overall results of the recognition process, the morphing and transient analysis as a precondition are outlined (Figures 19 and 20) below. In general, it can be stated that a low $\delta M$ is connected to a high similarity between the compared attractors.

**Figure 19:** $\delta M$ mean of the morphing analysis with according standard deviations sorted by subjects
Figure 19 shows all three $\delta M$ means of each subject separated into their individual boxes. The $\delta M$ mean represents the average of all results comparing a super attractor against the single running from minutes 11 to 20. It is evident that the general magnitude of the morphing process is rather small, lying in a range of $\delta M = 7$ to 14, and the individual values within single subjects do not vary to a great extent. From earlier studies, it is known that, if a running motion is joined by transient oscillations (Vieten & Weich, 2020), their impact very likely subsides by ten minutes. The procedure to visualize the transient effect was applied to a series of data sets in order to confirm this observation for the underlying data of the current study. Figure 20 shows a selection of four subjects derived from data taken from the current study with different initial transient oscillations. It can be seen that these oscillations level off before minute ten. The selections provided are severe cases and it should be noted that other subjects showed less or no transient effect. Summarized, all of the characteristic constants, derived from a curve fitting process, as described in (Vieten & Weich, 2020) and using the curve fitting software (CurveExpertPro, version 2.6.5, Hyams Development), can be seen in Table 12. This overview serves as guide values for future studies. Furthermore, the intervals in the current study can be classified as small.

Table 12: Overview of Characteristic Constants.

<table>
<thead>
<tr>
<th>Constant</th>
<th>$T_i$: Transient Effect’s Strength</th>
<th>$t_r$: Time for the Transient Effect Decreasing to $T \cdot e^{-t}$</th>
<th>$a_0$: Morphing’s Strength</th>
<th>$a_1$: Morphing’s Modulation Strength</th>
<th>$a_2$: Morphing’s Nonlinearity Strength</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-12.4-15.7</td>
<td>0.11-13.2</td>
<td>7-14</td>
<td>-0.39-39.6</td>
<td>0.09-1.69</td>
</tr>
</tbody>
</table>
4.5 Discussion

The hypothesis of the present study stated that a running person can be recognized from stride data derived from MEMS sensors attached to the ankles. The results indicate that the chance of having a false positive allocation is, on average, as small as 0.28%. Also meaningful is the high extent of subjects having the chance of being identified incorrectly is almost zero. Only two subjects were recognized incorrectly, with a probability of 5% or slightly higher. Consequently, the presumption of a gaitprint, defined as above and proposed in earlier works by (Broscheid et al., 2018; Byrnes et al., 2018; Vieten & Weich, 2020), can be highly confirmed. Morphing can deform an attractor in many different ways, which most probably results in $\delta M$s of comparable values as can be seen in Figure 19. This leads to the assumption that the impact of the morphing on the recognition process is at best marginal. Based on the outcome of (Vieten & Weich, 2020) and the analysis of the data that were collected for the current study, it was shown (Figure 20), that, although a person’s motion was accompanied by a transient effect at the onset, it subsided by 10 min. at the latest. For this reason, it can be expected that the running data from minute 11 until 20 are not influenced by transient oscillations. Thus, it can be assumed that the recognition analyses in this paper were not affected by the

Figure 20: Four examples (subject 10 = orange, 9 = green, 2 = blue, 5 = yellow) showing different progressions of transient oscillations which have subsided after minute 10.
transient effect. In addition, it should be taken into account that the influence of the transient effect could be linked to particular individual characteristics, such as the performance level. For example, Strohrmann, Harms, Troster, Hensler and Muller (2011) considered, among other things, the change in ground contact time within a step cycle. The participants were divided into performance groups based on their training kilometers and running speed. They ran at a running speed of 75–85 % VO2max, thus with a pace comparable to the 20 min. in the presented study. There were significant differences in the absolute value of the ground contact time (running beginners > running experts). While the contact time of the experienced runners levelled off after a few minutes, the contact time of the beginners increased over 15 min. until it remained stable until the end. While future investigations must be carried out to gain deeper information about the described transient process, the performance level data from the underlying study indicate that that the high recognition rate is also independent of training level expressed by an anaerobic threshold speed (between 10.4 and 16.1 km/h) and running hours per week (ranging from one to six hours).

Even though a very high recognition rate was observed when compared to the same subject, it is still evident that the recognition percentages between different subjects were low, but not zero. Regarding the general curve structure of the detection corridor (Figure 21, blue and orange line), a high concordance over all subjects can be seen. The distinct differences, meaning the variation in the similarity rates, are, consequently, due to the individual variations of the general course. This means that a common pattern and subject specific variations exist more or less within the limits (Figure 21, yellow line), generated as a range based on all subjects' data. The above described finding (see also Figure 21) is an indication for a general running pattern, which is inherent in all subjects representing universal running kinematics. Previous literature has mainly proposed two-part running cycles, namely stance and swing components, which can further be divided into sub-sections (Marquardt, 2012; Novacheck, 1998). According to this statement, running seems to be a quite global movement. Only by closer inspection, and applying a computer algorithm, can the individual differences be uncovered as a runner's unique gaitprint.
The current paper provides a basis to determine the characteristics of a well-developed running style. By applying the Attractor Method, it is possible to identify a person with a very high probability while only using their running motion. The next step is to determine, in which section of the general running cycle the greatest variation occurs.

![Graphs](image)

**Figure 21**: a–c. Display of the recognition horizon (blue and orange) with a data set from a differing subject over all three axes (Fig. 21a = x-axis, Fig. 21b = y-axis, Fig. 21c = z-axis). The recognition rate was 44%.

This would provide the basis for the identification between athletes. To what extent can these sections be subdivided into phases and can patterns be found that are related to highly successful athletes? Additionally, how can kinematic descriptions and physiological parameters, such as oxygen consumption at a given running speed, be connected? These are inspiring questions, the answers to which may be provided based on the present work. While these questions focus on a short-term time interval, sports science is generally also interested in considering these factors under the
influence of fatigue in the context of endurance disciplines. In other words, how do the kinematics of human running change over a long-term effort, like a marathon race? This is not only of interest concerning a stable running performance and the associated remaining high recognition rate, but also because of the increasing risk of injury, which could possibly be detected at an early stage. In a study conducted by Nicol, Komi and Marconnet (1991), the kinematic parameters of eight marathon runners were examined in a running test with three different speeds before and after the marathon event by video recording. While there were no meaningful differences at the group level, individual differences from pre to post were found. This is confirmed by earlier works, like the one by Williams, Snow and Agruss (1991), who also described the high individuality of kinematic parameters. These findings support the results of the present work. In the future it will have to be answered whether the recognition rate remains high, even with fatigue-induced individual kinematic changes.

Another highly useful application of the current findings could be in the recognition of athletes in the context of virtual racing series in e-sports, such as those practiced on ZWIFT (Zwift Inc., n.d.) or the IRONMAN virtual club (World Triathlon Corporation, 2020). These online applications invite athletes to global running and cycling events where they can participate from their living room equipped with a treadmill and a stationary bike. All of the machines are virtually connected so that the athletes can compete against each other. Further, it is possible to win not only virtual but also material prizes, possibly slots for a real-life world championship (Frye, 2020; Mackinnon, 2020). This possibly leads to an increasing rate of fraud attempts such as having a performance by another athlete who is in a better shape compared to oneself. To avoid this way of cheating, the current approach could offer the possibility of obtaining a baseline gaitprint, which could be easily recognized when performing later.

One limitation of the current study might be that the different sessions run by the same athlete always had the same speed, which could have led to an easier recognition due to more consistent motion kinematics. It is known that higher speeds are related to changes in stride length kinematics (Brughelli, Cronin, & Chaouachi, 2011; Mercer, Vance, Hreljac, & Hamill, 2002), leading to a higher variation within the data and, consequently, to a decreased probability of recognition. Thus, future work is necessary in order to minimize the recognition rate to an equally low level for the described recognition method. This is essential when desiring to apply the attractor method.
recognition approach in everyday life, or physically active situations, where natural speed changes occur continuously.

4.6 Conclusion

In summary, the Attractor Method approach allows for highly sensitive discriminations between runners with different performance prerequisites. In addition, the results of the current study show a general running pattern, which is so distinguishable through the individual characteristics of the participants, that a recognition rate of over 99% can be achieved. Based on this knowledge, future work can now gain deeper insight into applications regarding running quality, fatigue, and recognition, as in, for example, an esports context.

**Funding:** AFF-grand “cyclic human motion - 2019” of the University of Konstanz. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

**Acknowledgments:** We thank all subjects who participated in the study.

**Conflicts of Interest:** The authors have declared that no competing interests exist.

**Ethic statement:** The study was approved by the local Ethical Committee of the University of Konstanz, Germany under the RefNo: IRB20KN10-009.

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STUDY 4: The Attractor Method – A sensitive tool to highlight subtle differences in cross-country ski skating techniques (V1 vs. V2)

BOOK OF THE 8th INTERNATIONAL CONGRESS ON SCIENCE AND SKIING

Christian Weich, Stephanie Moore, Sten Fjeldheim & Randall L. Jensen

Bibliographic reference:
THE ATTRACTOR METHOD – A SENSITIVE TOOL TO HIGHLIGHT SUBTLE DIFFERENCES IN CROSS-COUNTRY SKI SKATING TECHNIQUES (V1 VS. V2)

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Keywords

cross-country skiing, skating technique, attractor method, roller skiing, technique analysis

5.1 Introduction

Distinguishing between various types of techniques used in cyclic sports is critical for technical and tactical analyses. Cross-country skiing is a traditional representative of cyclic winter sports, which can also be prominent during the summer months using roller skis. To perform adequately on various terrains, two different, primary, skating techniques have emerged. The V1 technique, mostly applied on hilly or high-resistance-low-speed sections, is characterized by one double-pole push every second stride. Whereas the V2 version, mostly used on flat tracks, is performed using a double-pole push during each single skate-push.

Former methods to analyze cyclic disciplines build upon stride analyses (Gohlitz et al., 1994), metabolic data and movement economy (Bonacci et al., 2010; Millet, Millet, Hofmann, & Candau, 2000), EMG studies (Chapman, Vicenzino, Blanch, Dowlan, & Hodges, 2008; Chapman et al., 2009), or non-linear time series and chaos theory (Lyapunov, 1992; Wurdeman, Myers, Jacobsen, & Stergiou, 2013). Lately, more cost-efficient methods working with acceleration sensors have found their way into technique analyses enabling discrimination between various physical activities (Skotte, Korshøj, Kristiansen, Hanisch, & Holtermann, 2014; Yang & Hsu, 2010), the successive parts of a stroke in swimming (Nakashima, Ohgi, Akiyama, & Kazami, 2010; Ohgi et al., 2002), and in the context of cross-country skiing between the gears
of the skating technique (Stöggl et al., 2014). Beyond classifying or distinguishing movement types or techniques, coaches are further interested in getting deeper insights into their athletes’ motion quality regarding, for instance, motion path, symmetry, or precision. The Attractor Method, developed by (Vieten et al., 2013) and (Vieten & Jensen, 2015), is an approach based on acceleration and gyrometer data to produce sensitive results allowing the objective analysis of subtle intra- and interpersonal changes of movement patterns and its variation.

The aim of the current study was to introduce the Attractor method as a tool to analyze group and individual differences in V1 and V2 skating techniques in cross-country-skiers. The group differences may highlight the key distinctions between both techniques whereas the individual analyses could provide useful information for coaches and scientists concerning personal stride characteristics with a goal of deriving an optimal movement.

5.2 Methods

A total of 16 athletes (Table 13), eight female and eight males, were tested from September through November 2018 in the lab of Northern Michigan University in Marquette, USA (MI). All participants were members of the elite cross-country team associated with the Northern Michigan University Division 1 Nordic skiing team. All participants were requested to fill out and sign an informed consent. Raw data collection was performed using five inertial sensors (RehaWatch; Hasomed. Magdeburg, Germany) which were attached to both ankles and wrists by a hook-and-loop fastener and tape. One further sensor was fixed by a shoulder strap at TH6 vertebrae to collect torso data. The sensors were 60x35x15 mm and weighed 35 g each. They functioned as a triaxial accelerometer with up to 16 G, a triaxial Gyroscope with up to 2 0 0 0 °·s⁻¹ and a magnetometer measuring with 1.3 Gauss. The possible measuring rate was up to 500 Hz and they were constructed as a micro-electro-mechanical system (MEMS). The recordings were gathered in three dimensions (x, y, z) with all data saved to

Figure 22: Performing skier
smartphones (Samsung Galaxy J5) using the app RehaGait Version 1.3.9 programmed by Hasomed (Magdeburg, Germany).

Table 13: Subject data.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Age (years)</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>8</td>
<td>20.5 ± 1.5</td>
<td>167.8 ± 5.6</td>
<td>62.7 ± 5.3</td>
</tr>
<tr>
<td>Male</td>
<td>8</td>
<td>21.9 ± 3.2</td>
<td>181.5 ± 8.0</td>
<td>73.2 ± 7.9</td>
</tr>
<tr>
<td>Overall</td>
<td>16</td>
<td>21.2 ± 2.5</td>
<td>175.0 ± 9.5</td>
<td>68.3 ± 7.9</td>
</tr>
</tbody>
</table>

To carry out the tests, the team skated with roller skis on an oversized treadmill (FitNex, 2.44 m x 3.05 m treadmill, Dallas, TX) and a ParvoMedics True One Metabolic System (OUSW 4.3.4) was used to measure the ventilatory data during all tests (Figure 22). The test series started with a graded VO2max test to determine each athlete’s maximum velocity (v\text{max} in m·s\(^{-1}\)), maximal oxygen consumption (VO2\text{max} in ml·kg\(^{-1}\)·min\(^{-1}\)) and the maximum grade (in % inclination). The initial performance test was followed by a second test day that included two sets of five-minute skating at the 85 % VO2\text{max} grade and stage. One bout was performed in the first technique, and after a five-minute wash-out break a second bout with the same duration was executed in the other technique. The order of both (V1 or V2) was randomly spread over all participants. The raw data collection occurred, as described earlier, with five accelerometers and a spirometer. The collected ventilatory data were not processed further in the present study. Further data management consisted of two main steps: The attractor calculations were based on the method described by (Vieten & Jensen, 2015; Vieten et al., 2013) and processed by a self-coded MATLAB app (The MathWorks Inc., Massachusetts, USA). All attractor data were converted to space-time curves (Figure 23), derived mathematically from the original accelerations and gyrometer data. Each body segment (legs, wrists and torso) had a representative 3D-attractor for each participant and both skating techniques (V1 and V2), which were compared overall by one-sample paired t-tests using Statistical Parametric Mapping based on the work of Pataky, Robinson and Vanrenterghem (2016). The statistical verification considered the skiing motion in three planes: forwards-backwards, side-to-side, and up-and-down, respectively. All statistical analyses were normalized on a defined starting point when the left ski of the respective athlete was at its most lateral point. In an exploratory analysis we also checked the attractor data for individual characteristics and hints for technical interventions.
5.3 Results

Table 14: Overall results V1 vs. V2 technique (L = left; R = right; given number = p value).

<table>
<thead>
<tr>
<th>Body part</th>
<th>Forwards - backwards</th>
<th>Up-down</th>
<th>Side-to-side</th>
</tr>
</thead>
<tbody>
<tr>
<td>Legs</td>
<td>Extreme points</td>
<td>Extreme points</td>
<td>Extreme points</td>
</tr>
<tr>
<td></td>
<td>(L &lt; 0.001 R &lt; 0.001 )</td>
<td>(L &lt; 0.001 R &lt; 0.05 )</td>
<td>(L &lt; 0.001 R &lt; 0.001 )</td>
</tr>
<tr>
<td>Arms</td>
<td>Extreme points</td>
<td>Extreme points</td>
<td>More arm motion in V2</td>
</tr>
<tr>
<td></td>
<td>(L &lt; 0.001 R &gt; 0.05 )</td>
<td>(L &lt; 0.001 R &gt; 0.05 )</td>
<td>(L &lt; 0.001 R &lt; 0.001 )</td>
</tr>
<tr>
<td>Torso</td>
<td>No diff. (&gt; 0.05)</td>
<td>Extreme points (&gt; 0.05)</td>
<td>Extreme points (&gt; 0.05)</td>
</tr>
</tbody>
</table>

Differences between the techniques were found primarily at the extremes of the movements (Table 14). These positions are defined as the outer most points in terms of their distance-time path in 3D motion, thus the coordinate where the sensors change direction to return to their initial position (Figure 23). The V2 technique was symmetrical, while for V1 the hang arm side was clearly evident for both arms and legs (Figure 23), but not for the torso (p > 0.05). The V1 technique had further reach to the extremes for both legs in all directions. There was also a difference for the side-to-side motion of the arms, where V2 showed a faster change from one pole placement to the other. The arms moving up/down and forwards-backwards did not differ on the right limb whereas the left pole showed significant differences in both directions. However, the torso did not result in any significant difference between the two techniques.

Beyond the characteristics of limb movement in the two techniques, the current study was also able to highlight technical individualities and qualitative variations comparing differently skilled skiers (Figure 23, dashed vs. solid curves). As examples for skill-related differences, Figure 23 shows a longer drive and glide phase for the pro skier (dashed), whereas the college level skier (solid) uses a shorter and more laterally reaching stride.
5.4 Discussion and conclusion

The main results of this work show that the global characteristics of each technique across the skiers were similar, however, specifics of the technique between skiers were able to be visualized. Both outcomes are in agreement with earlier works, such as Myklebust, Losnegard and Hallén (2014), who presented an approach, using accelerometers, to distinguish between V1 and V2. The differences in three-dimensional dynamics of the V1 and V2 strides may have significant importance when considering the primary goal of these techniques is forward propulsion. For example, a larger movement extreme of the ankle in the frontal plane (side-to-side) may indicate that the skier is displaying more lateral distance per stride, thus utilizing propulsive forces with reduced efficiency. Beyond the effectiveness of propulsion, the range of motion extremes in the sagittal plane have the potential to reflect differences in cycle rate associated with the V1 and V2 skating (Millet, Hoffman, Candau, & Clifford, 1998). Differences in the movement extremes in the current study were found with participants skiing at the same speed and grade, suggesting participants with less efficient movement patterns were likely generating more propulsive force to maintain a similar speed across the V1 and V2 techniques, as well as compared to more efficient skiers.
Further, larger extremes in the V1 technique could be seen because it is a movement that involves asymmetrical poling. In V1, we have a side that utilizes both, leg and poling power, at the same time and a side that is just utilizing a leg push off. Whereas in V2, the poling and skate push offs work together and are mirrored on both sides. Because of these technique differences, V2 typically shows a more direct movement down the trail and the skate push off will be quicker. V1 is characterized by a more lateral movement and a higher emphasis utilizing the glide in the skis. Because V1 technique is mainly used climbing hills, the speeds are slower and, in the field, (on a race course) this would mean a wider stance than in V2 and the direction or angle of the ski direction is a wider.
Moreover, in their perspectives section Myklebust et al. (2014, p. 892) proposed to use these modern devices as a direct training assessment tool for scientists, coaches and athletes. The present work followed this proposition utilizing the coaches of the NMU Nordic skiing team to analyze individual stride patterns and the motion variances between different performance levels, such as professional versus college level (Figure 23). The results were in accordance with independent video-analyses and the personal experience of the coaches. As an exploratory intervention over six weeks both athletes were given individual technique training based on their initial performance. In the follow-up test the pro athlete showed an almost identical movement pattern, attesting to a very persistent and automatized technique. Whereas the college athlete was now able to elongate the stride in the sagittal plane, especially in V1. This aligned the general propulsion toward a more forward orientation. Even though it is known for recreational and elite athletes that each skier performs in an individual manner, it might be a worthwhile aim to find an optimal stride or at least highlight stride phases that are associated with top performances. The hard- and software used in the current study allows for easy data acquisition in various sport-specific settings and environments, for example roller skiing on a treadmill could be compared with skiing on natural snow. These intersections between science and coaching demonstrate the practical relevance and usefulness of the presented method.

Although the presented approach can be described as an easy-to-use and cost-efficient way to analyze cyclic motion, the data management process is still very laborious and requires an extensive familiarization time. However, with the speed and potential of technological developments, this method could be assimilated into a user-friendly application in the future.

To sum up, the Attractor method is an appropriate tool to make raw data usable in practical sports assessments. The approach provided a general discrimination between V1 and V2 skating technique and further group and individual specific stride characteristics. Of superior value is the immediate transfer into practical training analyses and the simple visual representations for coaches and scientists.
6 General discussion of the results

The comprehensive aim of the current dissertation was the further development of the attractor method as a tool and software solution for the analysis of cyclic human motion in athletic contexts. The use of the attractor method approach made it possible to differentiate between the kinematic components of the cyclic movements studied. This facilitated a novel method of identifying persons; individuals could be differentiated only by their running behavior. Further, it enabled the assessment of subtle sport-specific movement patterns. The attractor method provides a linkage between modern cost-efficient hardware and a method packed into a simple software solution, thus allowing researchers to address contemporary issues in the field of sport science and rehabilitation. The implementation of modern sensors during training and competition in combination with versatile software approaches will be important for future research questions in sports science. The hypotheses evaluated in the core studies of this thesis support the modern advancement of cyclic movement analyses.

The first work (Vieten & Weich, 2020) represented the theoretical background for the subsequent publications of this dissertation. Here, the kinematic components of cyclic human motion, in particular running and cycling, were discussed. Subsequently, a mathematical model was presented, which encompassed six components of human motion: 1) the attractor (i.e. the average path of running/cycling movement), 2) the transient effect, 3) morphing, 4) short time fluctuations, 5) control mechanisms, and 6) technical noise. The derivation of the above-mentioned components was able to describe human running motion (hypothesis 1.1). The, by simulation, reconstructed raw data turned out to lead to very similar results compared to the originally measured ones (hypotheses 1.2 and 1.3). They differed slightly, only due to the influence of random components. Ultimately, a proof of concept for the mathematical model was supported by the validation of the running/cycling simulation data (hypothesis 1.3).

While the first study deals with all kinematic components of cyclic human movements, the second (a comparatively theoretical work (Weich, Vieten, et al., 2020)) proves the existence of the transient effect. This effect was often present at the beginning the measured running performances. It is characterized by an arrhythmic running behavior, which thereby affects the motion features of the lower kinematic chain and could be quantified by 3D attractors derived from acceleration data. Employing this
method, the transient effect was apparent in over 80 % of the recorded sessions (n = 60) and lasted approximately five minutes (hypotheses 2.1 and 2.2). These findings supported the irregular sensation at the beginning of a running session often reported by athletes. Contrary to expectations, the training level, the running experience, and the anthropometric preconditions had no significant relationship to the occurrence and extent of the transient effect (hypothesis 2.3). Nevertheless, the transient effect represents a measurable internal disturbance which, presumably neuromuscular, must be corrected at the beginning of a run. Thus, it remains exciting to see whether it becomes evident, and if so, to what magnitude the transient effect affects running performance, for example in a 10 km road race.

The two application studies (study 3: Weich & Vieten, 2020; study 4: Weich, Moore, et al., 2020) that made use of the attractor method to process recorded cyclic motion data support its application to healthy movement patterns. The resulting attractor calculation enabled the differentiation between individuals (study 3) and between two skating techniques (V1 and V2) in cross-country skiing (study 4). Specifically, the gaitprint study (study 3) supports the identification of runners only based on their running motion compared to all participants. This was achieved with a recognition rate of over 99 % and a false positive detection probability of only 0.28 % (hypothesis 3.1). The attractor method and the associated algorithms are thus a very sensitive method, which should be considered for future questions regarding person recognition, identification, but also in diagnostics. Thus, the differentiation between individuals and movement patterns is methodologically exceptional because it requires only two cost-efficient MEMS sensors and various self-programmed algorithms (which are free of charge available online). Therefore, a practical and efficient application for research, training, and competitive sports is an evident outcome from the current dissertation.

Despite the high degree of individuality, a general movement pattern for running was also determined using the attractor method (study 3). Individual deviations from this general pattern make each person’s movement unique (hypothesis 3.2). This also counts for the second application, a study conducted at Northern Michigan University with their cross-country skiing team (study 4). For this purpose, data acquisition of not more than five minutes skating per technique for each of the 16 skiers was sufficient. Here the attractor method was used to differentiate between two skating techniques in cross-country skiing (V1 and V2), both numerically and visually, by showing the coordinates of the skis, wrists, and torso (hypothesis 4.1). Further analysis showed
that these differences were especially recognizable at the extreme points of the skating movement. The latter positions are defined as the outer most points in their distance-time path, i.e. the coordinate where the sensors and therefore the limbs change direction. However, the data from the MEMS fixed at the torso showed no significant difference between V1 and V2. Based on the present work, it should therefore not be used as a sensor location for future technique analyses. Beyond this global analysis, the movement behavior of various individual athletes was also examined. Thereby, differences in skating technique between athletes of different levels were highlighted (hypothesis 4.2). These were in line with the video-based technique analyses of the head coach. Nevertheless, it must be emphasized that the latter analysis was an explorative approach that demonstrates potential for future development.

6.1 Developed apps for analysis using the attractor method

All studies are based on gathered acceleration and gyrometer data from MEMS sensors. These data were used to calculate attractors based on the original attractor studies (Vieten et al., 2013) and filtering processes (Vieten, 2004) of the research group led by Prof. Manfred Vieten. However, improvements and innovative applications of the attractor method required the development of new algorithms and corresponding applications in order to make the raw data manageable for the specific research questions. The following table (table 15) provides all developed applications and algorithms as well as a short overview of their main functions. These applications and algorithms were programmed by Christian Weich or Prof. Manfred Vieten (VietenDynamics) either individually or in cooperation. With the exception of the software tool Statfree, all applications and algorithms are programmed with MATLAB (The MathWorks Inc., Massachusetts, USA) and are provided free of charge:
### General discussion of the results

**Table 15: Overview of all apps/algorithms related to the attractor method**

<table>
<thead>
<tr>
<th>App / algorithm</th>
<th>Main function</th>
<th>Input Data</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Statfree software</strong></td>
<td>- Software package to manage and display data and mathematical functions</td>
<td>- csv or txt raw data</td>
<td>- Newly created or calculated data files or graphs can be saved as a new file</td>
</tr>
<tr>
<td>(version 8.4.1.0)</td>
<td>- Tool for creating and calculating attractors (later mostly replaced by the Attractor app)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Attractor app</strong></td>
<td>- Tool for creating and calculating attractors</td>
<td>- Acceleration raw data from two sensors, mostly left and right foot</td>
<td>- Main output: absolute D, δM, δD, δF (see chapter 1.2)</td>
</tr>
<tr>
<td>(version 3.0.1)</td>
<td>- Two attractors can be processed at a time</td>
<td></td>
<td>- Advanced output: Number of attractor data points for each attractor; Length of the attractor for each data set and combined</td>
</tr>
<tr>
<td></td>
<td>- Optionally an entire working directory can be processed successively</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Raw data and attractors can be visualized and rotated</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>CoordinateAttractor app</strong></td>
<td>- App to visualize and edit an attractor in its acceleration, velocity and coordinate space (simultaneously)</td>
<td>- Attractor data containing acceleration and gyrometer data</td>
<td>- All variations (acceleration, velocity, coordinates) can be saved with concordant time axis</td>
</tr>
<tr>
<td>(version 1.4.1)</td>
<td>- Was mainly used in the cross-country skating study to visualize path-time courses of limbs and torso (study 4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Separate editing of right and left attractor</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TrackSimulator app (version 1.7)</td>
<td>- App to produce multiple new raw data files by simulation based on the mathematical model introduced in study 1</td>
<td>- First and last minute attractor of any data set and a desired setting for the constants (see study 1)</td>
<td>- As a result of the simulation, the app will create a dataset of any size, which represents the defined attractor properties</td>
</tr>
<tr>
<td>---------------------------------</td>
<td>-------------------------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>SuperAtt algorithm (version October 2019)</td>
<td>- Algorithm to calculate a super attractor based on at least two attractor files</td>
<td>- Series of attractor data to be summarized to a super attractor (all data files must be in the same folder)</td>
<td>- Datafile as txt containing mean acceleration data of all axes and their recognition horizon defined as a tube around each attractor point with a distance of five standard deviations</td>
</tr>
<tr>
<td></td>
<td>- Processed can be all data formats available in attractor files (acceleration, gyrometer data, speed data, corresponding standard deviations) The also available CreateSuperMinute option made it possible to digitally extend the received super attractor (which represented only one cycle) to one-minute duration and the respective amount of cycles</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- The function of these algorithms was later automatized in the Transient app</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>SimilarityCheck algorithm (version March 2020)</strong></td>
<td><strong>Transient app (version 1.1.2)</strong></td>
<td><strong>CSVtoTXT app (version 1.0.1)</strong></td>
<td></td>
</tr>
<tr>
<td>---------------------------------------------------</td>
<td>----------------------------------</td>
<td>---------------------------------</td>
<td></td>
</tr>
<tr>
<td>- This algorithm checks one or multiple data to what extend their attractor lies within a separately chosen recognition horizon from a super attractor file</td>
<td>- Super attractor with recognition horizon and single/multiple data to check for similarity</td>
<td>- Recognition percentage of each comparison and the file names of data sets</td>
<td></td>
</tr>
<tr>
<td><strong>Transient app (version 1.1.2)</strong></td>
<td><strong>CSVtoTXT app (version 1.0.1)</strong></td>
<td><strong>SimilarityCheck algorithm (version March 2020)</strong></td>
<td></td>
</tr>
<tr>
<td>- App to analyze a series of data (mostly 60 single minute files) whether a transient effect is present (see study 2)</td>
<td>- App to convert .csv files to text files (TXT) which are applicable to the other apps mentioned above</td>
<td>- App to convert .csv files to text files (TXT) which are applicable to the other apps mentioned above</td>
<td></td>
</tr>
<tr>
<td>- Created or external super attractor can be used for analysis</td>
<td>- Series of attractor data to be checked for transient effect (all data files must be in the same folder)</td>
<td>- Single or multiple csv files (all data files must be in the same folder)</td>
<td></td>
</tr>
<tr>
<td>- Separate editing of right and left attractor possible</td>
<td></td>
<td>- Same number of TXT files as csv has been entered</td>
<td></td>
</tr>
<tr>
<td>- Number of attractor datapoints and filtering options are freely selectable</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Both FFT methods presented in this dissertation (study 2) can be applied</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>CSVtoTXT app (version 1.0.1)</strong></td>
<td><strong>SimilarityCheck algorithm (version March 2022)</strong></td>
<td><strong>Transient app (version 1.1.2)</strong></td>
<td></td>
</tr>
<tr>
<td>- App to convert .csv files to text files (TXT) which are applicable to the other apps mentioned above</td>
<td>- Super attractor with recognition horizon and single/multiple data to check for similarity</td>
<td>- Recognition percentage of each comparison and the file names of data sets</td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>CSVtoTXT app (version 1.0.1)</strong></td>
<td><strong>SimilarityCheck algorithm (version March 2022)</strong></td>
<td></td>
</tr>
<tr>
<td>- Single or multiple conversion possible</td>
<td>- App to convert .csv files to text files (TXT) which are applicable to the other apps mentioned above</td>
<td>- Super attractor with recognition horizon and single/multiple data to check for similarity</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Recognition percentage of each comparison and the file names of data sets</td>
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</tr>
<tr>
<td></td>
<td></td>
<td><strong>CSVtoTXT app (version 1.0.1)</strong></td>
<td><strong>SimilarityCheck algorithm (version March 2022)</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>- App to convert .csv files to text files (TXT) which are applicable to the other apps mentioned above</td>
<td>- Super attractor with recognition horizon and single/multiple data to check for similarity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Recognition percentage of each comparison and the file names of data sets</td>
<td></td>
</tr>
</tbody>
</table>
6.2 Using the attractor method to describe cyclic human motion

The attractor method proves itself to be an approach that allows the description of kinematic cyclic motions in the form of a mean sequence (attractor) without significant loss of information (Vieten & Jensen, 2015; Vieten et al., 2013). Originally, only two parameters were used to characterize the respective cyclic motion, which at the time was also limited to primarily walking and running. The first, $\delta M$, describes the normalized distance between two single attractors (e.g. one attractor of natural treadmill walking in comparison with another when walking with an additional cognitive task) (Vieten et al., 2013). Second, $\delta D$, allows researchers to interpret the changes of the movement variation. Therefore it is possible to show, for example, that weights attached to the ankles affect the movement precision negatively (Vieten et al., 2013, p. 6). In the course of time, the method has not only been applied in the context of healthy persons but has also been extended to the vital use in a clinical setting. The Fatigue Index Kliniken Schmieder (FKS), developed and described in Aida Sehle's doctoral thesis (Sehle, 2015), has since made an important contribution to the detection of motor fatigue, especially in MS and stroke patients (Sehle, Vieten, Mündermann, et al., 2014; Sehle, Vieten, Sailer, et al., 2014). Later, the FKS, abbreviated as $\delta F$, was also used in examinations with symptomatic lumbar spinal stenosis (sLSS) patients (Byrnes et al., 2018). Furthermore, Dettmers & DeLuca (2015) suggest that ‘this tool may serve as a model for the organic component of cognitive fatigue’ (p. 2). Therefore, the application for the attractor method has been well established, yet the extent of its contribution potential is not yet thoroughly explored.

The current doctoral dissertation supports the extension of the attractor method to sports performance and diagnostics. Thus, the next milestone was set in the paper of Vieten and Weich (2020); for the first time, five additional components were described in addition the individual attractor to further characterize the kinematics of human cyclic motion. This includes the quantification of components with random characteristics, which supports the well-known phrase 'repetition without repetition', formulated by Bernstein (1967) many decades ago. Further underpinning the inherent non-repeatability of the seemingly exact same movement. Hereby it is possible to quantify and describe human motion as it
occurs in nature. This applies to the analysis of groups as well as individuals. Moreover, the evaluation of the transient effect, which can be quantified and visualized at the beginning of a prolonged cyclic activity, such as running (Weich, Vieten, et al., 2020). Such an effect, especially at the beginning of a physical effort, can potentially influence the overall performance outcome. These findings possibly underline the importance of warming up, especially before endurance performances. Thus, it would be possible to start running with an individual rhythm or to run as close as doable to the individual attractor. It can be assumed that a more experienced athlete finds his or her rhythm faster than a novice, whose coordination and technical skills are, empirically seen, less developed. To what extent these components present their own characteristics during athletic activities or rehabilitation (i.e. with irregular movement patterns) is a potential topic for future investigation. Further applications, especially those with practical relevance, are described in the following sections.

### 6.3 Applying the attractor method to identify persons and specific movements

The approach to identify persons (Kale & Patil, 2016) or sport specific techniques like strokes in swimming (Nakashima et al., 2010) and skate styles in cross-country skiing (Stöggl et al., 2014) using sensor technology is not a new concept. Movement differentiation has been employed in the context of safety and health aspects (Ciuti, Ricotti, Menciassi, & Dario, 2015), technical executions in sports (Nakashima et al., 2010; Skotte et al., 2014; Stöggl et al., 2014) or in the e-sports/e-learning sector (Bratitsis & Kandroudi, 2014). In order to achieve enough precision to correctly register and identify persons and/or their movements, a loss-free acquisition and processing of large amounts of data is required. Here the attractor method and the corresponding recognition applications developed in part during the course of the current dissertation (see table 15) have proven to be tools with high reliability. The gaitprint study (Weich & Vieten, 2020) reported a detection rate of 99 % and a false positive probability of detection of only 0.28 % in all subjects tested. Furthermore, in the study with cross-country ski athletes (Weich et al., 2020) it was possible to differentiate their skiing style (V1 or V2) solely on the basis of MEMS sensor data. This was
especially true with performance information from both, their arms and legs. While further investigations and improvements will be necessary before any subsequent use, especially in security systems. The latter sector may be particularly interested in the unique identification of a person or a movement from a judicial point of view, for correct control of the digital avatar or in terms of sportive fairness. Within the context of the underlying dissertation, a general practicality has been demonstrated in these two studies.

6.4 The attractor method as a tool to analyze sport-specific techniques

Technique analyses in sports have always been carried out; running or walking economically saves energy, thus improves performance and a technically clean way of moving also prevents injuries. Initially, it started with basic observations like counting steps and later progressed into slow-motion recordings extending further to camera- or sensor-supported systems that are still being developed today (see chapter 1.1 regarding the history of gait analysis). The attractor method pushes the innovative line further with the CoordinateAttractor application (table 15). Its ability to reveal technical differences in cross-country skiing style facilitates technology-driven training interventions to enhance individual performance (Weich, Moore, et al., 2020).

By using the CoordinateAttractor app, a live analysis (in which the individual cycles are drawn on a monitor) could also be integrated in the future projects. These single cycles could then be visually compared to the individualized attractor. For example, the cycles representing current motion could be compared to the individual attractor to help to detect performance and injury related variables like fatigue. Hypothetically, this could be labeled in relation to a threshold of deviation from a long-term attractor (i.e. super attractor over several measurements recorded over months or years). Analogous to the previous chapter, it is quite exciting to extend the potential of the method to differentiating athletic performance (beginner vs. professional), special technical abilities, or performance deterioration via the attractor or its components. The foundations were laid through the fundamental works of the current dissertation,
although further improvements can be made and tested with regard to its application in individual analyses.
7 Limitations and methodological evaluation

General remarks

In principle, efforts have always been made to cover a broad spectrum of the population in terms of gender, age range, and level of performance. All test persons were healthy adults and more or less experienced in sports. Yet this also means that the results presented in this paper are thus far only valid for these specific populations. The methodology presented is surely relevant for use with children, the elderly, or patients, however the specifics of its transferability would require further research and validation. An extensive demonstration that the attractor method is also important in clinical settings is provided by Aida Sehle in her dissertation (Sehle, 2015).

All studies presented included only healthy subjects with a natural running style. Right-left differences were of course possible but should not lie outside the range of variations of a healthy human person. Moreover, it must be considered that running in natural and outside environments, like woods, on roads or even on a track can differ vastly from lab settings chosen in the works of this dissertation. External influences, such as uneven surfaces, gradients or weather conditions may lead to disturbances of the individual running rhythm. In order to be able to continue running on these surfaces, internal feedback mechanisms are necessary. A similar impact would also be caused by internal, in some cases pathological, disorders, e.g. triggered by neurological incidents, such as a stroke. Thus, it would be interesting to see to what extent pathological or other non-systematic fluctuations in motion patterns affect the robustness of the outcomes observed. Should the latter be confirmed in future studies, the presented methodology can be regarded as a valid instrument to realistically observe running or walking behavior.

Regarding the type of sport, the data was mainly collected during running. In order to be able to make a more extensive assertion on cyclic human motion, more data have to be recorded also during cycling and cross-country skiing, as well as other sports such as rowing, swimming or skating (on ice or road). One could even use a movement from a typically acyclic sport, like a tennis swing, and to repeat this several times. It is well known that all these sports have
different emphasis on the mainly recruited muscle groups and also on intra- and intermuscular coordination. Marquart (2012, p. 89) provides examples for the difference between walking and running motion. Further Myers (2015) based on his Anatomy Trains, describes various types of sports and other movements (pp. 255–283). These insights possibly lead to variable demands and executions, e.g. impaired by the proportion of active working muscles or the number of degrees of freedom. Broadening the application field of the attractor method to several cyclic sports would certainly reinforce its general validity for cyclic human movements.

A further issue is the design of the exercise intensity, which in all studies corresponded to a continuous load between five and 60 minutes. The running/skating speed and the cycling power were always kept constant to reduce variability throughout the data. Thus, the influence of the running speed could be eliminated to observe the potential changes in running characteristics independently of the pace. However, if you consider pacing in a regular running training or competition, such a consistent intensity as on the treadmill or a bicycle ergometer is very unusual (Thompson, 2015). In order to be able to declare the presented results even more practically relevant, further studies with variable and/or changing intensities are required.

In addition to the general remarks described above, further specific comments on the individual studies follow below:

**Study 1: Vieten & Weich, 2020**

The data acquisition of at least five 60-minute sessions per each participant, results in an extensive database that is representative of the recruited test persons. Nevertheless, the sample is limited in that it consists of only ten persons. Thus, the model should be validated on additional participants in future works. As already suggested in the paper itself, a clinical application can also be considered. Further validation is necessary for a transferability into clinical applications. The authors propose (p. 40) that the FKS described in the works of Aida Sehle (Sehle, Vieten, Mündermann, et al., 2014; Sehle, Vieten, Sailer, et al., 2014) can be improved using the presented findings especially with respect
to the morphing component. Until these changes are realized, a usage in the described clinical context is limited.

The recognition horizon of five standard deviations and the settings for the simulation variables in the TrackSimulator app (table 15) (which was not derived from the curve fitting), were ultimately determined according to trial and error and best practice. As can be seen from the reported results, the selection was certainly reasonable, however further “best-practice” evaluations can be determined by comparing all possible configurations with machine-based algorithms.

The differentiation between the recognition of the same and all different subjects was, as defined in the text, based on the results. This revealed a clear separation (pp. 34-35; Figs 3 & 4), which discriminates the same from other subjects. A key objective of future refinements of the presented methodology is the determination of a threshold percentage, to determine when compared attractors correspond to the same participant. The authors suggest using the median method, which was described in (Vieten et al., 2013, p. 4). In addition, the subsequent publication about the gaitprint (Weich & Vieten, 2020) already presented optimizations that could also be applied in the context of potential revisions of Study 1.

**Study 2: Weich, Vieten, et al., 2020**

The third research question (hypothesis 2.3) delves into the potential impact of running performance and experience on the occurrence and duration of transient effect. No relationship was found in the present study; however, the performance and experience data were only collected via a short questionnaire. For a more thorough and diverse comparison, it would be essential to collect objective performance data in future studies based on sports science diagnostics. Subjective evaluations, especially of athletes, as in this case, always run the risk of being biased due to social perceptions and desires (Brenner & DeLamater, 2014).

Furthermore, the cutoff of the intra-class coefficient (ICC) for the presence of the transient effect was set to \( r = 0.7 \). The fundamental basis for this was provided by Hopkins (2000) which is originally not based on sport scientific or
biomechanical data. For potential future evaluations of the transient effect, a discipline-specific classification should be discussed. Ultimately, the question remains which physical and/or mental mechanisms might cause the transient effect. To clarify this would encourage the understanding of whether and to what extent the transient effect influences performance. In the study included in this dissertation, the focus lay fully on the quantification of this effect. Only the simultaneous recording of other physiological variables, such as oxygen consumption or muscle activity (EMG) can provide holistic answers about the origin of the transient effect.

Study 3: Weich & M. Vieten, 2020
Although the gaitprint method has been proven very sensitive, the method presented here involves the entire attractor sequence. Though, the sensitivity may alter for different parts of the gait cycle. This would then possibly uncover insights, which portions are general, and which are rather person specific. Thinking in the context of clinical applications, it could be possible that various diseases may also have typical characteristics that affect the movement only partially. Examples are potential hemiplegia or weakness of dorsiflexion of the foot after a neurological disorder such as a stroke (Kramers de Quervein, Simon, Leurgans, Pease, & McAllister, 1996). Because the comparison process is performed pointwise anyway, it is reasonable to modify the algorithm for future research into smaller analysis segments. This segmentation could be logically based on scientifically supported running-cycle models as discussed for example in Marquart (2012) or Novacheck (1998). Still, the current study already provides the framework to undergo a distinct recognition process.

Study 4: Weich, Moore, et al., 2020
The cross-country study performed at NMU delivers quite interesting results but must be classified as rather explorative methodologically. Particularly, in the case analyses, only a few individual skiers were considered. Nevertheless, it should be emphasized that the findings are very hands-on, and they rationalize the realization of a study with a larger sample size. A further limitation in the final study was in that the data recordings lasted only five minutes. Considering the findings of the second study, it is especially
possible in the first five to ten minutes the transient effect can affect a movement pattern significantly (Weich, Vieten, et al., 2020). Even if the individual attractor was not changed in its fundamental character, major influences cannot be excluded with certainty. Accordingly, in future studies, the sessions should last at least twenty minutes, and if possible, longer.

So far, we focused primarily on MEMS data which cannot provide holistic information to, for example, evaluate the economy of the movement. In contrast to the other works of this dissertation, ventilatory data (via spiroergometry) was collected during the entire duration of the experiment. Although these data were not included in this publication, a relationship was discovered between motion economy (rate of oxygen consumption) and the movement variability (operationalized by $\delta D$, introduced earlier in this thesis) when comparing the V1 and V2 skate techniques (Moore, Weich, Torchia, & Jensen, 2020). Specifically, it was found that the variability of torso movement was correlated to the economy of movement, thereby providing evidence that the method could be used within the context of competition analyses. Thus, beside quantitative results, conclusions about the quality of movement could be drawn. The inclusion of additional physiological data sources with the attractor method can provide further insights into the complex understandings of the human body.
8 Conclusion

The current thesis is composed of four published works that broaden the application of the attractor method. The first describes the kinematic basis of cyclic human motion (Vieten & Weich, 2020). The general conception, multiple approaches, software development, and the final data collection of this study were the most wide-ranging of the entire dissertation. This largely comprised the working hours of the first two thirds of the PhD, which then provided a foundation for all of the further works. Besides the actual movement attractor, five components were described based on this publication: the transient effect, attractor morphing, short-term fluctuations, a control mechanism, and technical noise (p. 20).

In the second study (Weich et al., 2020), it was shown that an initial arrhythmic movement behavior, related to the running style, was found in most of the participating athletes. This altered behavior, technically termed as the transient effect, typically diminished after a few minutes. However, appearance and duration of this effect are not related to the experience and level of an athlete. Even though the attractor method is a very general and versatile tool, especially for clinical use, the focus of the underlying dissertation was placed on further development with regard to athletic performance analyses. An essential part of this was the three-month research project with the cross-country skiing team of the Northern Michigan University in Marquette. Here, the attractor method was used for the first time as a tool for analyzing sport-specific technique (Weich, Moore et al., 2020). Within the scope of this project, quantitative as well as visual insights into the cross-country skiing technique were highlighted and evaluated at group and individual level. It was particularly satisfying, that the results obtained were in line with the experiences and impressions of the team's trainers who had already been working with the team for many years. The second application study (Weich & Vieten, 2020) provides the essential mathematical frameworks for a better understanding of athletic and general movements by outlining ways to identify individuals and running motion itself based on MEMS data creating a gaitprint (p. 65). Additionally, the findings open up possibilities for other broader applications, such as security systems, e-sports, or e-learning. In support of these purposes, we were able to show that the attractor method
and the associated recognition algorithms with a detection rate of 99 % may be a very suitable tool. Considering all of the described works that constitute this dissertation, very important contributions have been made to the fundamental understanding of athletic movements that originate from cyclic sports. Further, significant progress has been made regarding collection and analysis of these movements. Finally, a number of smaller studies within the theoretical papers and especially the two application-oriented research works prove a very powerful potential of the attractor method.
9 Future considerations

As with most doctoral dissertations, you can't foresee at the beginning where the work will take you and where the horizon will end. Ultimately, this work’s framework provides fundamental research and approaches. Expectedly, some questions still remain, while new ones have also emerged. A number of considerations, especially for competitive sports, are listed below:

- For the basic attractor parameters, $\delta M$ and $\delta D$, standard values could be established. This would allow researchers to objectively determine whether two compared attractors (and thus individual motion sequences) are more or less similar in their characteristics and variation.

- Table 15 summarizes all self-programmed apps and algorithms. It would be preferable to combine all useful functions related to the attractor method in one comprehensive software.

- In addition to the transient effect and the morphing, the other kinematic components of cyclic human motion can be studied in greater depth in a separate work. This would provide an even better understanding of the principles of human motion.

- It is further of interest if there are any similar findings to the transient effect or morphing, i.e. variations of the individual attractor, adjustments of measurable physiological parameters, such as EMG or oxygen uptake. If so, it should be assessed if these show deviations in running (movement) economy. In this way, answers regarding the quality of the running movement could be provided.

- We were able to achieve a very high level of recognition by the evaluation the gaitprint at a constant running speed. However, in order to be able to generalize the approach, the methodology must also be adopted for variable running speeds.
• The final study showed that the attractor method is also very well applicable to a sport other than running or cycling (cross-country skiing). In the future, it could also be used to address research questions in any cyclic sports, even in swimming (a waterproof hardware is also available).

If the methodology and the corresponding applications will be further developed and simplified in future, they will certainly be interesting not only for sports scientists and for clinical usage. Especially coaches, therapists and also the athletes or patients themselves can benefit from these analyses. It is also quite feasible to implement the method in sports technology, for example in activity trackers, watches, or with MEMS sensors that can be integrated into shoes or clothes.
10 Contributions to the original works

The present work is a cumulative dissertation. The latter includes all the original works listed below. All articles have been published in international journals or books and have been evaluated according to the peer review procedure. In the following section, the personal work contribution is illustrated for all co-working authors. The checkmark ✓ indicates where involvement of the author listed was credited.
10.1 STUDY 1: The kinematics of cyclic human movement

Bibliography:

Lead authorship: Manfred M. Vieten
Co-authorship: Christian Weich

Table 16: Author contributions study 1

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10.2 STUDY 2: Transient effect at the onset of human running

Bibliography:

Lead authorship: Christian Weich
Co-authorship: Manfred M. Vieten, Randall L. Jensen

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10.3 STUDY 3: The Gaitprint – Identifying individuals by their running

Bibliography:

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Co-authorship: Manfred M. Vieten

Table 18: Author contributions study 3

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10.4 STUDY 4: The Attractor Method – A sensitive tool to highlight subtle differences in cross-country ski skating techniques (V1 vs. V2)

Bibliography:

Lead authorship: Christian Weich
Co-authorship: Stephanie R. Moore, Sten Fjeldheim, Randall L. Jensen

Table 19: Author contributions study 4

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