Running Deciphered

van Oeveren, B.T.

2021

document version
Publisher's PDF, also known as Version of record

Link to publication in VU Research Portal

citation for published version (APA)
van Oeveren, B. T. (2021). *Running Deciphered: The interpretation of running technique from wearable data*. [, Vrije Universiteit Amsterdam].

English summary

In Europe, almost 13% of the population regularly runs, which makes running one of the most popular sportive activities in Europe and also in the Netherlands. The popularity of running can be explained by the positive effects on health and the accessibility of the sport. Paradoxically, running also belongs to the topmost injury susceptible sports. Anno 2020, it is difficult to imagine running without wearable technology such as sports watches, smartphones and activity trackers. With embedded GPS, accelerometers and heartrate monitors, runners collect valuable data on training volume, intensity and running technique, each training. Wearable feedback devices allow timely corrections in training behaviour and running technique and has, therefore, the potential to improve performance and reduce injury risk.

A correct interpretation of training data is essential, eventually to advance performances and reduce injuries. Erroneous instructions resulting from measurement errors or misinterpretation could harm performance and even accelerate injury development. Because of the repetitive movement, in a cyclic sport like running, a small adjustment in mechanical load per step may have a significant impact on injury risk, efficiency (energy cost per distance) and performance. Task-oriented instructions, like those on running technique, are therefore required to regulate training load and thereby reduce injury risk. However, the current technology provides feedback strongly focussed on long term goals like distance- and speed targets. In addition, measurement errors and the absence of contextual information in the analysis prevent a correct, clear-cut interpretation.

Running technique is dependent on the interaction between biomechanical factors, individual characteristics and situational circumstances. These contextual constraints make it difficult to provide accurate feedback and instructions to the runner on the optimal running technique for a specific situation. The contextual factors and measurement errors are even under experimental conditions challenging for the feedback accuracy. The natural dynamic context in which wearable devices capture training data favours the ecological validity. However, the diverse context poses a challenge for the interpretation of the collected data.

Within the data process, from measurement to the interpretation, the research in this dissertation aimed to find solutions to improve the accuracy, the personalisation and interpretation of wearable data in running. The ultimate goal of this research is to empower high-quality feedback on running in future applications ensure that technology can be used to reduce injuries and improve personal performance.

Stride detection from an acceleration signal

Accelerometers are typically embedded in wearables for movement detection. For many cyclic endurance sports, such as walking, running, cycling, speed skating, cross-country skiing, and rowing, the detection of the fundamental movement frequency provides, the basis for feedback. For example, activity trackers count the number of steps in walking and in running the step frequency is captured. In addition, the detection of the movement frequency provides the basis for many algorithms to extract additional parameters. For example, the vertical displacement is calculated per step and ground contact time is part of the step duration. A sensor that is placed perfectly at the midline on the chest will be suitable for measuring steps. Alternatively, a sensor that is placed on the foot will be suitable to measure strides (two sequential steps). However, for many sensors positions an asymmetry in the signal may result in an algorithm that inconsistently detects steps or strides. Furthermore, movement artifacts and other causes of irregularities in the recorded signal may result in detection errors. Consequently, a smartphone carried in the trouser pocket, or an activity tracker carried around the wrist may yield inaccurate results. The accuracy of detection thus depends on the sensor's position, orientation, fixation, weight and dimensions. The accuracy and versatility of the algorithm can be improved when the algorithm identifies complete cycles independent of its orientation. In walking and running, a gait cycle is called a 'stride' and consists of a left and right step. In **Chapter 2**, a new adaptive algorithm for stride detection is described and validated. It validates sequential cycles and resulted in excellent performance under varying conditions and with virtually no effects of sensor orientation and position. The algorithm is designed to work in real-time on a smartphone or any other sensor. The algorithm can theoretically be used for other cyclic activities.

Speed from contact time and GPS

Besides improvements in parameter detection, is it possible to improve the accuracy of feedback by combining data from various sensors, also known as 'data fusion'. Due to sensor fusion, the limitations of one sensor can be corrected for by another sensor. The measurement of speed is very relevant for a runner since it allows to get insight on the intensity, running technique and efficiency of the run. Speed is typically derived from GPS position. With GPS, a position error of 5 to 15m can be expected. The measurement error in position affects the derived speed. The GPS-speed can specifically be expected to be poor in situations with poor satellite reception especially when the trajectory consists of sharp turns or during accelerations. It is known that step frequency and ground contact time relate with running speed. Step frequency and contact time are typically measured with sensors placed on the feet or chest. Therefore, in contrast to GPS, the accuracy of step frequency and contact time are not subject to signal transmission issues. In **Chapter 3**, we study whether the possibility to estimate and validate speed using step frequency and contact time. To this end, we compare the speed based on GPS and ground contact time with the speed measured with a stopwatch. We conclude that especially speed based on contact time may provide a useful method to validate or replace speed based on GPS, in circumstances where GPS speed is expected to be inaccurate.

An energetic optimum based on heart rate

In general, it is desirable to have a running technique that requires low energy cost. Previous studies have shown that an energetically optimal stride frequency can be determined from oxygen consumption or heart rate. Most experienced runners prefer a stride frequency near their energetically optimal stride frequency. Novice runners, on the other hand, tend to run below their energetically optimal stride frequency. It is known that stride frequency is speed dependent. The same can be expected for the optimal stride frequency. In **Chapter 4**, we study if the energetically optimal stride frequency can be determined at various running speeds. In line with previous findings, the novice runners in the study seemed to decrease heart rate by increasing their stride frequency. In contrast with expectations, both the optimal and the preferred stride frequency were not found to increase with running speed. The absence of speed dependence can be explained by the limited speed range that is common to novice runners and the relatively low number of observations in the study. Nevertheless, the results suggest that it is not imperative to take the small effect of running speed on the optimal stride frequency into account for novice runners.

Inter-individual differences in stride frequency

Stride frequency is one of the most used parameters of running technique. There is a persistent belief among trainers and runners that stride frequency should be 90 steps per minute. This belief entails that the 'optimal' stride frequency is independent of running speed and the context. Furthermore, it assumes that the optimum is the same for everyone. In **Chapter 5**, we used years of training data (representing 16.128 hours) collected by 256 users of sports watches. We investigated the factors that affect the inter-individual differences in the stride frequency–speed relationship. Leg length, age, Body Mass Index and weekly training volume were found to have a significant effect on the stride frequency- speed relationship. In contrast to what is commonly assumed, injury prevalence, running experience and performance did not reveal a significant relationship with the measured stride frequencies. These findings imply that running speed should be taken into account along with leg length for an accurate interpretation of stride frequency. To a lesser extent, age, Body Mass Index and weekly training volume may be considered.

Running styles from wearable data

The current feedback on the running technique is usually limited to isolated biomechanical parameters, leaving the interpretation to the runner. Several researchers have pointed out before that multiple parameters are required to characterise a running style. Each parameter describes only one characteristic of a complex gait pattern. The fact that many parameters are interdependent must be acknowledged for an adequate interpretation which does not appear to be applied by default. Yet, even in scientific studies, the dependency between parameters is not always appropriately considered. In the synthetic review of **Chapter 6**, we studied what set of parameters describes the fundamental differences between running styles. A runner intends to move his body in forward direction, the body centre of mass describes thereby a sinusoidal trajectory. We reasoned that the parameters required to describe an asymmetry of the sinusoidal trajectory of the body's centre of mass in running would reveal the fundamental characteristics of running styles. We conclude that at a given speed, the stride frequency and the duty factor will be sufficient to identify most fundamental differences in running styles. Where duty factor can be calculated from contact time and the step frequency and represents the ratio between the contact time and the flight time. When comparisons between runners are made, we advise to normalise step frequency by leg length. To allow easy interpretation, we propose the use of a so-called 'Dual-axis model', which combines the step frequency and duty factor in a model. With the 'Dual-axis model', we explain the characteristics of the five most distinct running styles. This Dual-axis model creates a practical guide to measure and interpret the running technique.

Profile of runners

It is critical to use a suitable reference population to avoid misunderstandings when runners are compared. In **Chapter 7,** we investigated how 1802 runners differ from each other in terms of training behaviour, injuries and motivation. It is important to stress that these runners would typically be labelled as 'recreational' runner in most studies. In our analysis, the participants were divided into three groups based on a self-reported 10km time adjusted for age and gender. We found substantial differences between the three performance groups in training behaviour, injuries and motivation. For the less fast runners, weight loss proved to be a relatively common reason to run regularly. The faster runners were more motivated by improving endurance and participating in running events. As expected, the faster runners trained more often and covered greater distances. Also, faster runners participated more frequently in interval training.

Conclusions regarding injury prevalence were strongly dependent on how the injury prevalence was expressed. For example, the faster runners were found to have higher total injuries rates. However, there were no differences between the groups in the injury prevalence per unit of time (injuries expressed per 1000 h) and fewer injuries among the faster runners when the prevalence was expressed per running distance (injuries expressed per 1000 km). Faster runners had relatively more injuries around the Achilles tendon. The lower injury prevalence with higher training volume and speed in the faster runners, together with the differences in injury location may imply differences in running technique between performance groups.

In the current analysis, there appear to be performance-dependent differences within the large group of runners in this study, who would typically be categorised as 'recreational' in the literature. The results show that the commonly used category 'recreational' is not sufficiently specific and that comparisons between runners should not be made based on this label. Benchmarking feedback based on the performance level is thereby a practical solution to provide runners with personally relevant guidance and instructions.

Conclusions and practical considerations

The studies in this dissertation result in several practical solutions to improve the accuracy and interpretation of wearable data regarding running technique. We can propose the following practical recommendations:

- The various studies in this dissertation have shown that speed should not be ignored for the interpretation of running technique and that a single isolated biomechanical parameter is insufficient to characterise a running style. Based on the Dual-axis model from **Chapter 6**, we expect that fundamental differences between running styles can be characterised by measuring (merely) speed, stride frequency and contact time. We expect the Dual-axis model to have important implications for follow-up research and feedback design.
- The accuracy with which steps are detected can be improved by using the algorithm from **Chapter 2**. However, for most situations in running, a high accuracy of stride frequency and contact time can be expected when sensors are positioned conveniently.
- In particular, improvements in estimating speed based on GPS are desirable. Validation of among others, GPS-based speed can be done by merging data, as suggested in **Chapter 3**. The relationships derived from aggregated datasets provides a generic solution to validate the quality of the data (**Chapter 5**). **Chapter 6** shows that step frequency and duty factor can predict the movement of the body centre of mass. Duty factor can be calculated from step frequency and contact time. Therefore, in theory, step frequency in combination with contact time could be used for the validation of GPS-based speed.

- Determining an energetic optimum using imposed stride frequencies seems to be an auspicious way to provide targeted feedback **(Chapter 4).** To this end, the runner must vary stride frequency sufficiently at a given speed and within a specific context. Because an obtained optimal stride frequency is context-bound (e.g. weather conditions, terrain, physical condition) generalisation will be limited, and an expected margin of error should be taken into account.
- Reference values can be obtained from population datasets, individual data or based on an energetic optimum. Each of these methods has its pros and cons **(Chapter 8).** Based on **Chapter 7,** we can say that for a comparison based on population data, the reference population must correspond sufficiently to the runner(s) in question.
- Because many factors are related to running performance, it would be obvious to make comparisons between runners with only small differences in performance. The minor performance differences would stimulate the runner to make only small adjustments in running technique or training behaviour.
- In **Chapter 8,** we argue that it is inadvisable to work unilaterally towards specific target values for two reasons:
    - Due to measurement errors, individual and contextual differences, a target value will always have shortcomings.
    - Based on the literature, we expect that unilaterally working towards a target value is ineffective in developing new skills, adaptability and self-optimisation. Instead, we believe that feedback should encourage variation.
- We think that with the Dual-axis model, the fundamental differences in running styles can be explained. Therefore, we recommend future studies to focus on the validation of the Dual-axis model and then study the effects of contextual factors, individual factors and adjustments in running technique in relation to this proposed model.

- Despite the improvements yet to be made in wearable feedback of commercial products, it seems elusive to take all sources of variation into account. Moreover, in **Chapter 8**, we argue that a putative generic optimal movement solution is not only elusive but may also be ineffective. Researchers suggest that variation, a vast repertoire of movement possibilities, and variability, the selection of a movement pattern from among the possibilities, are essential to boost motor learning and prevent injuries. We, therefore, recommend future studies to not only explain the sources of variation, but also focus on the (biomechanical) effects of self-initiated gait adjustments, the effects of variation on the learning process and on the development of local fatigue. If the assumed role of variation and variability on learning and adaptation prove to be correct, fundamental changes may have to be made in the feedback design to stimulate runners to explore new behaviour.