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Capturing the Complex Relationship Between Internal and External Training Load: A Data-Driven Approach

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Background: Training load is typically described in terms of internal and external load. Investigating the coupling of internal and external training load is relevant to many sports. Here, continuous kernel-density estimation (KDE) may be a valuable tool to capture and visualize this coupling. ***Aim:*** Using training load data in speed skating, we evaluated how well bivariate KDE plots describe the coupling of internal and external load and differentiate between specific training sessions, compared to training impulse scores or intensity distribution into training zones. ***Methods:*** On-ice training sessions of 18 young (sub)elite speed skaters were monitored for velocity and heart rate during 2 consecutive seasons. Training session types were obtained from the coach's training scheme, including endurance, interval, tempo, and sprint sessions. Differences in training load between session types were assessed using Kruskal–Wallis or Kolmogorov–Smirnov tests for training impulse and KDE scores, respectively. ***Results:*** Training impulse scores were not different between training session types, except for extensive endurance sessions. However, all training session types differed when comparing KDEs for heart rate and velocity (both $P < .001$). In addition, 2D KDE plots of heart rate and velocity provide detailed insights into the (subtle differences in) coupling of internal and external training load that could not be obtained by 2D plots using training zones. ***Conclusion:*** 2D KDE plots provide a valuable tool to visualize and inform coaches on the (subtle differences in) coupling of internal and external training load for training sessions. This will help coaches design better training schemes aiming at desired training adaptations.

Keywords: training load monitoring, data science, big data, kernel density estimation, KDE, heart rate, velocity, speed skating

Daily training monitoring informs coaches and athletes on the effectiveness of training sessions, which enables them to steer training adaptations for optimization of athletic goals and performance.[1] To this end, continuous monitoring of training load (both in terms of internal and external load) is critically important, helping to determine whether athletes are adapting to training stimuli or if fatigue accumulates (which may lead to overuse injuries), in which case training schedules should be adapted.[2] External training load refers to the physical work performed by the athlete in terms of the quantity, quality, and organization of exercise (eg, measured by velocity, power or acceleration), whereas internal training load is defined as the psychophysiological response to the external load during exercise (eg, measured by heart rate, lactate or rating of perceived exertion [RPE]).[1,3] It is advised to analyze both internal and external training load variables for sufficient insights into training stress.[2] However, there is no current standard for directly coupling internal and external training load that highlights underlying patterns and which is easy to visualize to enhance understanding of the stimulus of specific training sessions.

Training load monitoring is mostly used to evaluate the overall fitness or fatigue of athletes, for example, by comparing alignment of internal and external load measures. For each training session, the coach aims to achieve an intended training stimulus by prescribing a specific external training load. For example, with extensive endurance training the coach asks athletes to exercise at a low intensity that can be sustained for hours (ie, at velocities corresponding to a heart rate between ~60% and 80% of maximal heart rate and a blood lactate below 2 mmol·L^{-1}).[4] If an athlete repeats the exact same session (same external load) and experiences a lower internal load in the second bout, this could point to adaptation. If, on the other hand, the athlete experiences a higher internal load, this could point to accumulated fatigue, disturbed well-being, or illness or overreaching (although this response may be more complex for submaximal heart rate during overreaching). By comparing internal and external load parameters, coaches can evaluate whether their training prescription did actually result in the intended stimulus.

Often, internal and external training load are summarized in one overall score for a training session, such as session RPE, training impulse (TRIMP) scores, or power or distance covered.[1] Studies have investigated the relationships between overall scores for internal and external load, demonstrating that these are positively related, but also that the relationship depends on training type.[5] However, summarizing internal and external training load values into one overall score or into different training zones—which is commonly done—simplifies the time series of a training session and may lead to a loss of information and/or distinction between different training sessions. Therefore, in addition to quantifying training load into one overall score or into training zones, we propose a new standard that directly couples all data points of internal and external training load within a training

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session using 2-dimensional (2D) kernel density estimation (KDE) plots, also known as Parzen's window.[6]

KDE is a nonparametric method to describe the distribution of a parameter by estimating the unknown probability density function of the data.[7] KDE represents the continuous distribution of a parameter, which could replace the discrete histogram, and visualizes underlying patterns and irregularities in the data.[8] As a practical example, one could map the heart rate and velocity time series within extensive interval sessions via KDE and examine exactly at what percentage of maximal heart rate and maximal velocity the intervals are carried out. Combining bivariate KDEs of internal and external load measures will provide "a template" for how these measures are related, and may, therefore, be a novel tool to discover differences in training load of specific training sessions. While KDE is regularly applied in an environmental[9] and health context,[10] applications in sports are sparse. To the best of our knowledge, only a few studies used KDE in a sport context, and only to describe player position on the pitch in soccer[11] and rugby.[12] It remains unknown whether KDE also reveals valuable information on the coupling between internal and external training load, which may benefit coaches and support staff in designing their training schemes.

In this study, we propose 2D KDE plots as an analysis tool for the coupling of internal and external training load parameters. Using 2 years of training load data from competitive speed skaters, we aimed to evaluate how well KDE visualizes training monitoring data and differentiates between training sessions in comparison to commonly used approaches, such as TRIMP scores or intensity distributions based on training zones.

Methods

Subjects

Eighteen national speed skaters participated in this study. Speed skaters were of elite and subelite level and included 10 females (age: 19 [1] y, bodyweight: 66.0 [3.8] kg, height: 1.74 [0.03] m, $\dot{V}O_2$ max: 50.3 [4.4] $mL \cdot kg^{-1} \cdot min^{-1}$) and 8 males (age: 20 [1] y, bodyweight: 72.1 [7.7] kg, height: 1.83 [0.06] m, $\dot{V}O_2$ max: 60.6 [8.5] $mL \cdot kg^{-1} \cdot min^{-1}$). The study was approved by the ethics committee of the University of Groningen (UMCG, Department of Human Movement Sciences, protocol code ECB/2017.07.21_1R1), and the experimental design, benefits, and possible risks of participation were explained to the participants before signing their informed consent. The study was conducted according to the Declaration of Helsinki (2013).

Design

This is a retrospective longitudinal study. Within a speed skating team, the training of speed skating sessions was monitored for internal training load (ie, heart rate) and external training load (ie, velocity) during 2 consecutive competitive seasons (2018/2019 and 2019/2020). Training data were obtained at the teams' home ice rink.

Methodology

Internal training load was obtained via heart rate, measured continuously in beats per minute throughout the training sessions using a Polar Team2 chest strap (Polar Electro Oy). Only heart rate values recorded between the start and end of a training session were included for analysis.

External training load was measured in terms of velocity attained throughout the speed skating sessions. Velocity was collected using 12 local detection loops (X2 timing and data system, MYLAPS bv) positioned at 11.6 to 55.2 m distance between loops within the 400-m ice rink where the skaters performed their training sessions (for details see Roete et al[13]). Skaters wore a transponder strapped around their ankle (MYLAPS Prochip Classic) to determine the time each loop was passed, with a high resolution (±0.003 s). Velocity was calculated by dividing the distance between 2 consecutive loops by the time difference of passing these loops (in kilometer per hour). If the time between 2 consecutive loops on the same day differed by more than 1 hour, these were considered to belong to different training sessions. Since training is generally performed in the inner lane, the distances between loops belonging to the inner lane were used to determine the velocity.

Training types of the prescribed speed skating sessions (n = 933) were retrieved from the coach's training scheme. These include extensive endurance, extensive interval, intensive endurance, intensive interval, tempo, sprint, and other sessions.

Data Analysis

To quantify training intensity distribution, both velocity and heart rate values were expressed relative to their maximal values and within training zones. To avoid unrealistically high maximal values that could be based on outliers, we used the 99.9th percentiles instead of the true maximal values within the 2 competitive seasons. Velocity values were expressed in 5 velocity zones based on the active moments of training (defined as velocities ≥14.4 $km \cdot h^{-1}$), including zone 1: 0% to 20%, zone 2: 20% to 40%, zone 3: 40% to 60%, zone 4: 60% to 80%, and zone 5: 80% to 100% of the active velocity range.[13] All velocity values below 14.4 $km \cdot h^{-1}$ were considered to be inactive moments (ie, zone 0). Relative heart rate values were expressed in 5 heart rate zones corresponding to Edwards TRIMP, including zone 1: 50% to 60%, zone 2: 60% to 70%, zone 3: 70% to 80%, zone 4: 80% to 90%, and zone 5: 90% to 100% of the maximal heart rate.[14] Heart rate values below 50% of maximal heart rate were considered as zone 0. For each training session type, Edward's TRIMP scores were calculated based on the time spent in each of the 5 heart rate zones,[14] in line with the original TRIMP approach for combining exercise intensity and duration.[15,16]

Velocity and heart rate data were synchronized based on their timestamps for every athlete. Velocity values for a segment were excluded when skaters skated in reverse direction. Heart rate data were then joined to the velocity data based on the athlete identifier and their timestamps, while accounting for daylight saving time. To assess direct coupling between heart rate and velocity time series, we accounted for the phase lag between the 2 signals that was identified based on cross-correlation (ie, 8-s time delay for heart rate). This resulted in a combined data set with values of both internal and external training load at each passing (of a loop in the ice rink). Subsequently, distribution of the data for specific training session types could be evaluated continuously using kernel density scores or after binning into discrete velocity and heart rate zones. For this analysis, we only included training session types that (1) aimed to trigger physiological adaptations, (2) had the entire session concentrated on this purpose, and (3) included at least 25 sessions in the data set. These training types are extensive endurance, intensive endurance, extensive interval, intensive interval, tempo, and sprint sessions.

Kernel Density Estimation

KDE was used to estimate the probability density function from the actual observations, while applying a kernel bandwidth as smoothening parameter.[6,7] Bandwidths were derived from normal scale methods[17] and corresponded to 1.5 km·h^{-1} for velocity and 1 beats·min^{-1} for heart rate data. Bivariate plots were created for the discrete zones and continuous KDEs of the velocity and heart rate data. In addition, to directly compare the combination of internal and external load between specific training sessions, 2D KDEs were subtracted between 2 training types (using the R-function kde2d from the *MASS package*).

Statistical Analysis

Data are presented as mean (SD). Normality of the data was evaluated using the Shapiro–Wilk test. TRIMP scores were compared between specific training sessions using a 1-way analysis of variance or Kruskal–Wallis tests (if the data are not normally distributed). Post hoc tests were performed to detect differences between training session types, after Bonferroni correction. In addition, training intensity distribution within specific training sessions was obtained by binning the data into velocity[13] and heart rate zones[14] or using the KDEs of velocity and heart rate. To compare KDEs for velocity and heart rate between the specific training types, a permutation test of equality was performed using the R-function sm.density.compare from the (smoothing methods) *sm package*.[18] If these indicated significant differences, pairwise post hoc tests were performed using the nonparametric 2-sample Kolmogorov–Smirnov test to localize the differences between training session types. Bonferroni corrections were applied to account for multiple testing. Effect sizes of the differences in heart rate and velocity between training sessions types were analyzed using the Kolmogorov distance statistic or Cohen *d* statistic. Results are considered to be significant if $P < .05$. All (statistical) analyses are performed in R (version 4.0.0; 2020-04-24).

Results

Training Sessions

Speed skaters completed 933 training sessions over the 2 competitive seasons, including 118 extensive endurance sessions, 40 intensive endurance sessions, 180 extensive interval sessions, 28 intensive interval sessions, 169 tempo sessions, and 80 sprint sessions. For each training session type, representative descriptions, anticipated RPE scores and their frequency in the data set have been provided (Table 1). Average TRIMP scores were presented for each training session type in Figure 1.

Visualization of Internal and External Training Load

Focusing on training load distributions for specific training session types, both internal and external training load can be visualized using heart rate and velocity data. As an example, distribution of heart rate data from all intensive interval training sessions was displayed in Figure 2, which can be presented after binning the data into discrete training zones (Figure 2A) or as continuous KDEs (Figure 2B). The same can be done for velocity data (Figure 2C and 2D, respectively). Also, the coupling of internal and external training load distributions can be visualized using bivariate plots, both in terms of discrete training zones (Figure 2E) or continuous KDEs (Figure 2F). Figure 2 illustrates that the 2D KDE plot reveals a more detailed visualization of the training load compared with 2D plots using discrete training zones. Figure 3 displays the 2D KDE plots for each training session type. For example, it can be observed that extensive endurance sessions are predominantly performed around ~75% of maximal velocity (V_{max}) and ~85% to 95% of maximal heart rate (HR_{max}).

Differences in Training Load Between Training Session Types

Interestingly, the overall TRIMP scores did not differ between training session types, except for a higher TRIMP score during extensive endurance sessions (Figure 1). In contrast, comparing KDE distributions of training load between training session types reveals that these differ significantly for heart rate and velocity (both $P < .001$). Pairwise comparisons of KDEs for heart rate and velocity reveals that all training session types are different from each other ($P < .001$ for heart rate and $P < .001$ for velocity; for effect sizes, see Supplementary Material [available online]). Importantly, pairwise comparisons can also be visualized using 2D KDE plots, by subtracting 2D density estimates of 2 specific session types, such as presented in Figure 4. For instance, comparison of intensive and extensive interval sessions (Figure 4A) reveals that intensive interval sessions are performed more at ~95% of V_{max} and

Table 1 Training Prescription, Anticipated RPE Scores, and Frequency for Each Training Session Type in the Data Set

Training	Description	Expected RPE (CR-10)	Frequency, %
Extensive endurance	3 × 12 laps with 6 min of rest (males) 3 × 8 laps with 6 min of rest (females)	4	19.2
Intensive endurance	6 × 8 laps with 6 min of rest (males) 6 × 5 laps with 7 min of rest (females)	7	6.5
Extensive interval	2 × 400-600-800-600-400 m (deep posture) with 6 min of rest 2 × 120 m (very deep posture)	5	29.3
Intensive interval	4 × 600-1000 m with 8 min of rest + 3 × 800 m with 8 min of rest	7	4.6
Sprint	3 × 100-100-100 m (straight) with 4 min of rest 3 × 100-100-100 m (turn) with 4 min of rest 3 × gliding start + 200 m with 4 min of rest	5	12.0
Tempo	5 × 800 m with 8 min of rest	8	27.5

Abbreviations: CR-10, 10-point category-ratio scale; RPE, rating of perceived exertion.

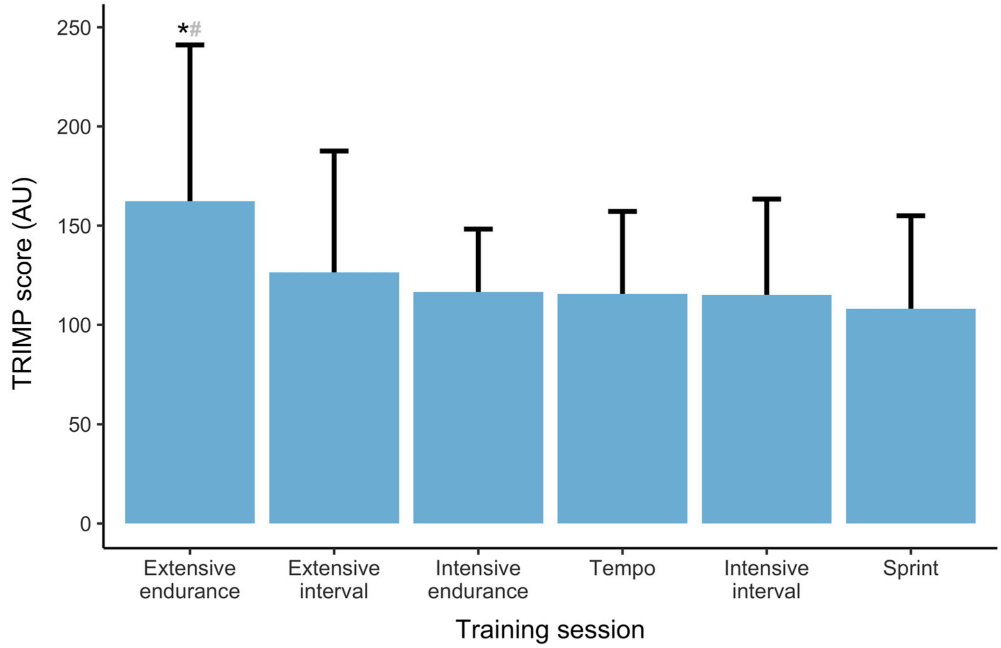

Figure 1 — Training load is presented for each training session type based on their overall TRIMP scores. *Differences in TRIMP between extensive endurance and all other session types, $P < .05$. #A tendency for difference in TRIMP between extensive endurance and intensive endurance sessions, $P = .08$. TRIMP indicates training impulse.

95% HR_{max}, while extensive interval sessions concentrate around 70% V_{max} and 80% HR_{max} and around 85% V_{max} and 90% HR_{max}. Notably, load differences between training session types do not map one-on-one to the discretized training zones, and 2D KDE plots visualize differences also when these are more subtle (ie, occur across or within the borders of specific training zones). Therefore, 2D KDE plots provide detailed insights into the differences in internal and external training load between training session types that are relevant for coaches when prescribing exercise to their athletes.

Discussion

In the present study, we introduced 2D KDE plots to visualize the coupling of internal and external training load data and evaluated how well these differentiate between training sessions in comparison to traditional approaches, such as TRIMP scores or intensity distributions based on training zones. Whereas TRIMP scores were similar between training session types (except for extensive endurance), KDEs revealed significant differences in training load between each of the training session types. This study is the first to show that 2D KDE plots provided a detailed representation of the training load of specific training sessions.

Training load monitoring provides essential information to coaches when prescribing training sessions to their athletes, as training load parameters can be useful to evaluate injuries, illness, or overtraining.[19–23] Even though it is recommended to assess both internal and external training load parameters for sufficient insights into training stress,[2] few studies have investigated the direct relationship between internal and external load, and mostly in terms of their correlations[5,24] or ratio[25] using one score per (training) session. However, simplifying the time series data within sessions into one summary score may come at a cost of losing relevant information. Indeed, our findings show that overall TRIMP scores were not able to differentiate between training session types (except for the extensive endurance sessions), whereas differences between all training session types *are* observed for continuous KDEs of the training load parameters. Figure 2 shows that for intensive interval sessions, the skater's velocity has a bimodal distribution with peaks around ~75% and ~20% of maximal velocity, corresponding to actual intensive skating and casual skating (in between bouts of exercise). For the discrete training zones, this corresponds to zones 3 to 4 and zones 0 to 1, respectively. For heart rate, there was only one peak around ~80% of maximal heart rate, corresponding to training zones 3 to 4, likely because heart rate will remain elevated over short breaks in between bouts of the intermittent exercises. In this study, we demonstrate that the direct coupling between internal and external load for specific training sessions can be visualized using 2D KDE plots. Such 2D KDE plots preserve training load distributions within the specific training sessions, revealing a detailed presentation of the load coupling. For intensive interval sessions, we show that intervals are mostly executed at 70% to 85% V_{max} and 85% to 95% HR_{max}, which is more precise than the bivariate plots based on training zones (Figure 2E–2F). Interestingly, extensive endurance sessions in speed skating were focused around 75% V_{max} and 90% HR_{max} (Figure 3), which is below race velocities, but more intense than the 60% to 80% HR_{max} that is expected for this type of endurance training in endurance athletes.[4] Of note, submaximal heart rate values may be 15 to 20 beats·min^{-1} higher in speed/inline skating compared to other endurance sports,[26,27] likely due the prolonged duty cycle of the skating stroke that compromises the blood flow.[28] Moreover, the heart rate intensities we observed corresponded to the intensity that is regularly used by speed skaters during their endurance training (~90%–95% HR_{max}).[29] By using 2D KDE plots, internal and external load can also be directly compared between 2 types of training sessions, by subtracting their density estimates (Figure 4). Such visualizations provide additional

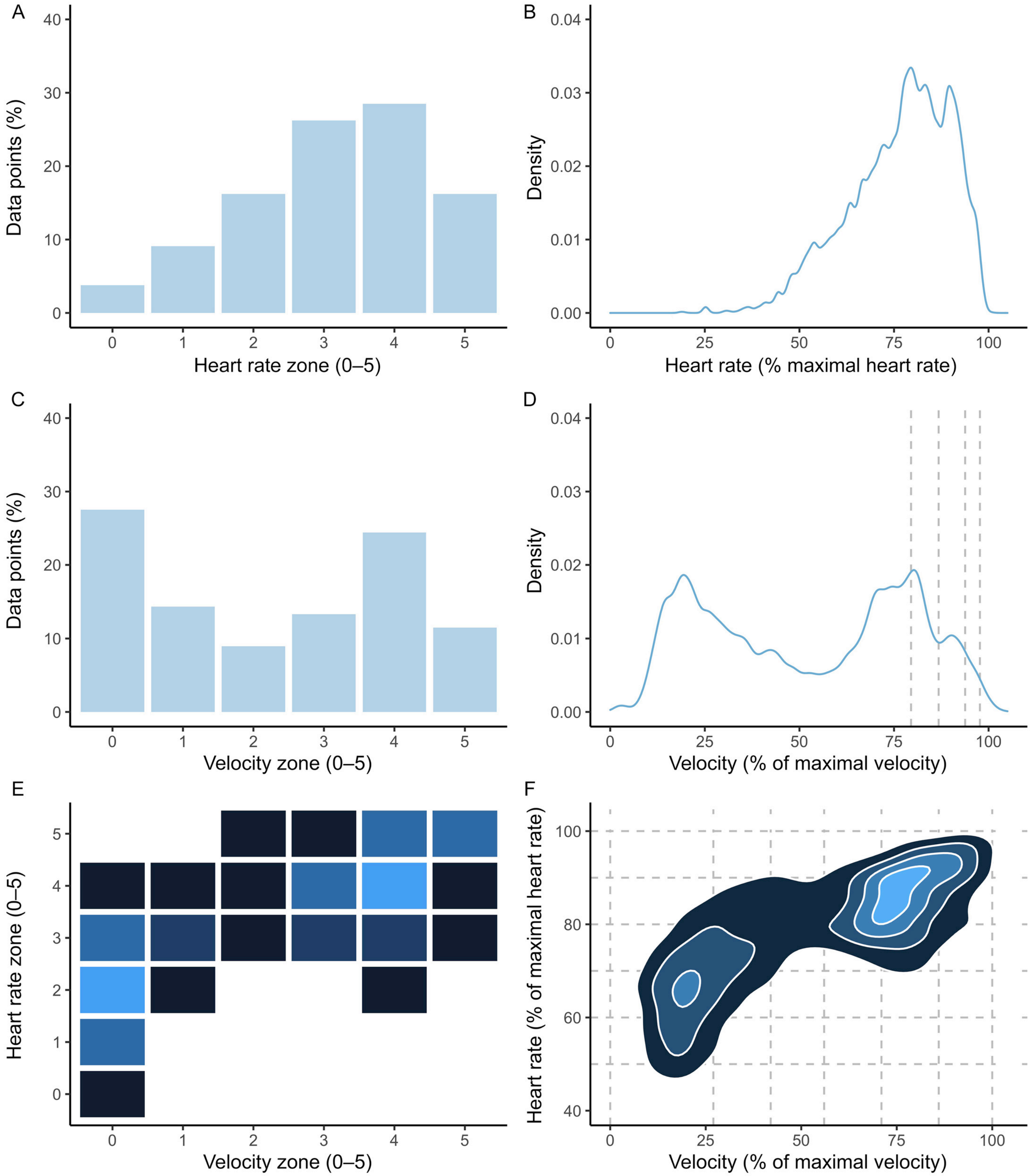

Figure 2 — Training intensity distribution of heart rate and velocity data was presented for all intensive interval training sessions, after binning the data into discrete heart rate zones[14] (A) or velocity zones[13] (C) or as continuous KDEs based on the percentage of maximal heart rate (B) or maximal velocity (D). Direct coupling of internal and external training load distributions was visualized using bivariate 2D plots, both in terms of discrete training zones (E) or continuous KDEs (F). The lighter shade indicates more frequent occurrence of that combination of heart rate and velocity zones or intensities. Boundaries of the heart rate and velocity zones are indicated using grid lines. Data points were collected at the passing of each detection loop in the ice rink (12 times per lap). Reference values for competitive velocities were obtained from top-10 finishers competing in the same age category as our speed skaters (neoseniors) during the National Championships within the corresponding season. These reference values are presented in panel D by vertical lines for 500 m (98% of maximal velocity), 1000 m (94% of maximal velocity), 1500 m (87% of maximal velocity)—all excluding the start—and 3000 m/5000 m (80% of maximal velocity; in females/males). KDE indicates kernel-density estimate.

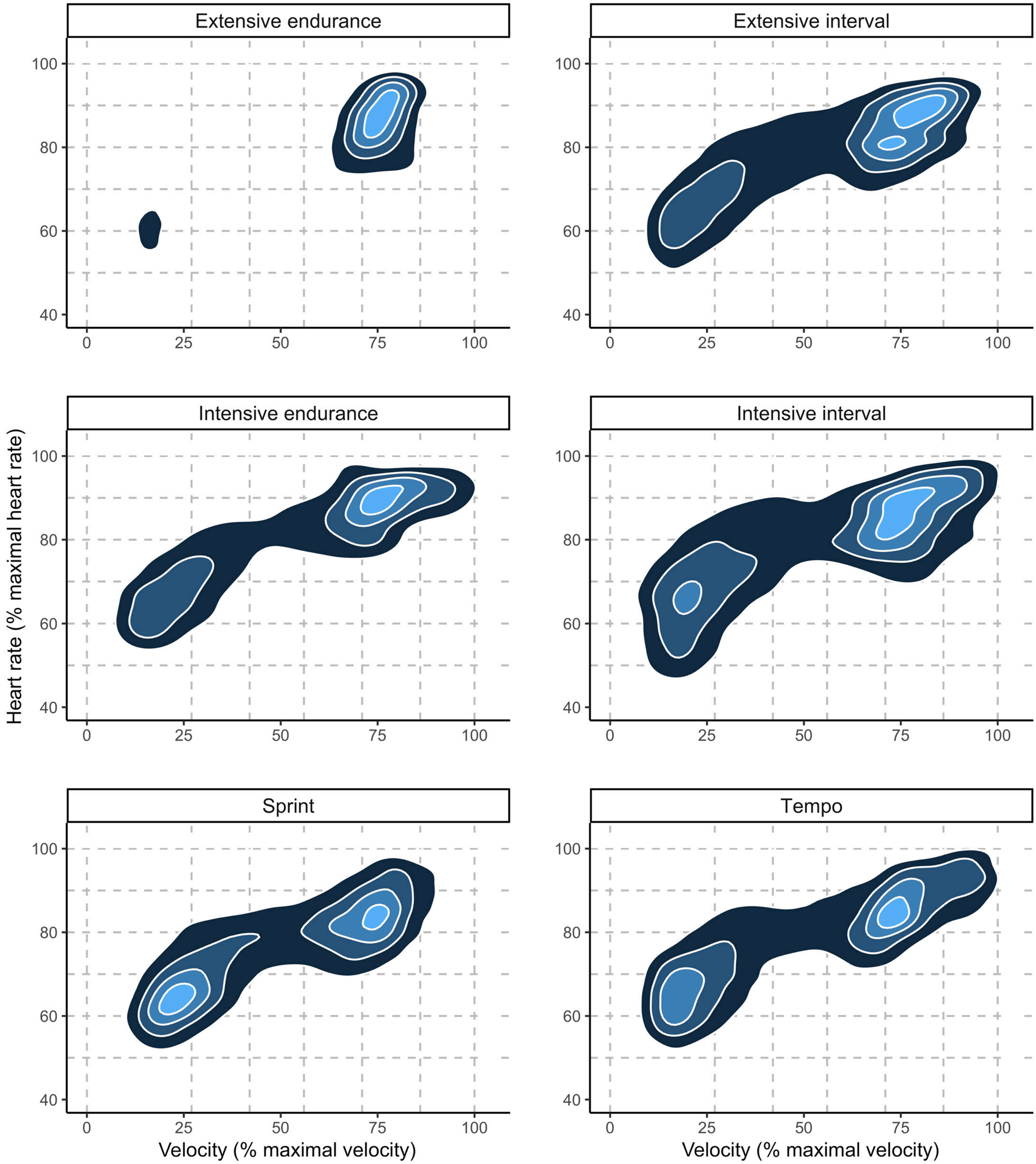

Figure 3 — Direct coupling of internal and external load of specific training session types was visualized using 2D kernel-density-estimate plots based on heart rate (in % of maximal heart rate) and velocity (in % of maximal velocity). The lighter shade indicates more frequent occurrence of that combination of heart rate and velocity intensities. Boundaries of the heart rate and velocity zones are indicated using grid lines. Data points were collected at the passing of each detection loop in the ice rink (12 times per lap).

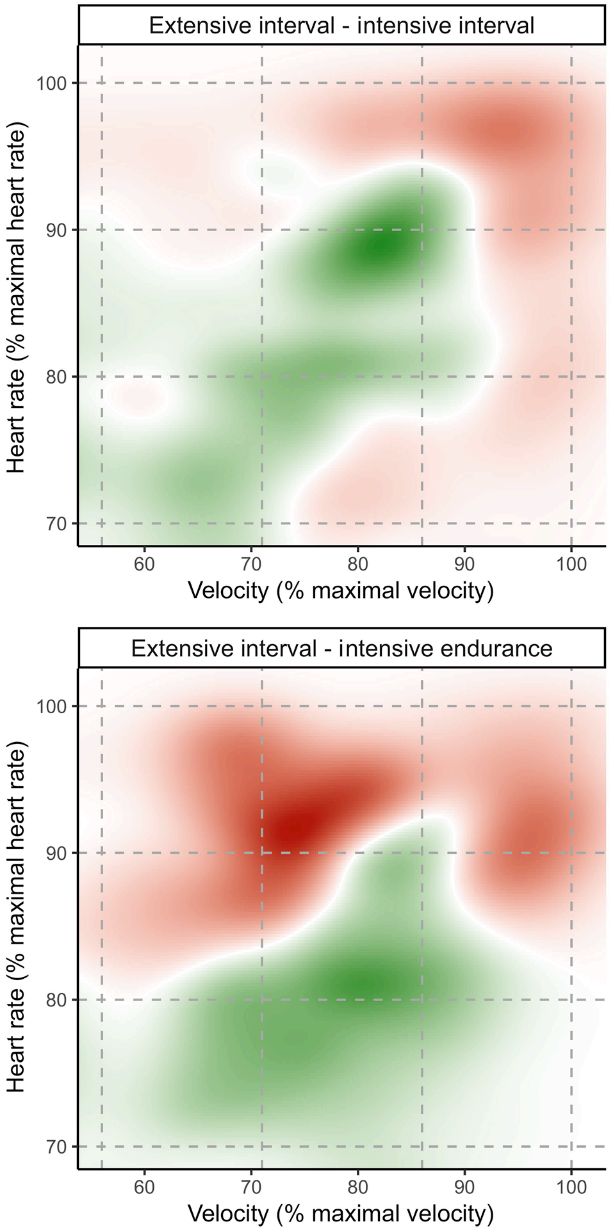

Figure 4 — The pairwise comparison of internal and external training load between 2 training session types is visualized using 2D KDE plots. Comparisons were established by subtracting the 2D KDEs of one training session type from that of another training session type. Larger differences are illustrated by darker colors. Differences were displayed for the range of heart rate values corresponding to heart rate zones 3 to 5 and the range of velocity values corresponding to velocity zones 3 to 5. Heart rate and velocity intensities in the (left) bottom occur more frequently during extensive interval sessions (in green), whereas the other combinations of heart rate and velocity intensities in the top (right) occur more frequently during intensive interval or intensive endurance sessions, respectively (in red). See online article for color version of the figure. Boundaries of the heart rate and velocity zones are indicated using grid lines. KDE indicates kernel-density estimate.

and detailed insights into the (subtle) differences in training load between training session types. In brief, we argue that 2D KDE plots provide a new and valuable tool for analyzing the direct coupling between internal and external load. This enables more precise monitoring of athletes and planning of training sessions by coaches.

To the best of our knowledge, this study is the first to investigate the direct coupling between internal and external load using 2D KDE plots and the first to examine the direct coupling of internal and external load in speed skating. 2D KDE plots have been used before, to investigate spatial trends of attacking possession in rugby,[12] and the team's space-related control on the pitch in soccer.[11] This highlights the general ability of KDE plots to visualize and summarize complex time series data. However, big data sets are required to provide sufficient data points to create such detailed visualizations. For instance, the study of Martens et al[11] incorporated 54 soccer matches with 31,824 data points and that of Sawczuk et al[12] included 138 rugby matches comprising 99,966 data points. In the present study, we monitored competitive speed skaters for 2 consecutive seasons and obtained detailed sensor readings from heart rate monitors and detection loops on the ice rink, which resulted in a data set of 933 training sessions with 421,982 data points (at least 11,821 data points per training session type). Naturally, applying 2D KDE plots to investigate the direct coupling of internal and external load may be very promising for other sports as well. For example, in cycling, running and rowing—where large amounts of high-resolution data on heart rate, velocity, and power are collected—these bivariate KDE visualizations will likely also lead to new insights into the monitoring and prescription of training load.

Considering the specific training load parameters that are used to create the 2D KDE plots and the resolution at which the data are collected is important when comparing 2D KDE plots between session types or between sports. For example, instead of heart rate, the widely used RPE scores could also be collected to quantify internal training load in terms of session RPE load (ie, intensity × duration).[30] In that case, it is advised to use RPE scales that have more options, as these may provide more detailed measures of exercise intensity.[31,32] The downside of using RPE scores—instead of higher resolution heart rate data—is that typically one RPE score is given for each training session, which requires researchers to obtain many data points by collecting many sessions from a large number of athletes or over many competitive seasons. Alternatively, RPE and velocity could be obtained within training sessions after specific elements (eg, intervals) to increase the resolution. In this study, we obtained heart rate and velocity data when passing the detection loops in the ice rink. Although heart rate was available at a higher resolution (1 Hz), we decided not to upsample the velocity data to 1 Hz as that would only lead to duplication of velocity values. From a practical perspective, visualizing 2D KDE plots based on heart rate and velocity data obtained when skaters pass a detection loop (12 times per lap) has the advantage that it provides a good reference for speed skating applications that inform coaches with real-time feedback.[33]

Practical Application

Our method of profiling training load distributions using 2D KDE plots of the various training session types can be of great value to the coach involved. First of all, quantifying the internal and external load over a longer period will help to assess the *actual* training load experienced by the athletes. Second, the bivariate KDE plots show the coach in great detail what the load of a particular training type is, which might in fact be quite different from the *intended* training load. Differences in *perceived* and *intended* training load are relevant for training optimization, as these may relate to different perceptions of success, personal accomplishment, recovery, and self-regulation.[34] Third, pairwise comparison of 2D KDE plots of specific training session types point out (subtle) differences, such as between intensive interval and extensive interval sessions, which could lead to further refining the training set-up. As such, our method will help coaches to assess and fine-tune their training designs, and potentially identify cases of suboptimal training load in individual athletes.

Conclusion

This study shows that the 2D KDE plot provides a useful tool to visualize and quantify the complex coupling of internal and external load of specific training sessions. Based on heart rate and velocity data, we demonstrate (subtle differences in) load between specific training sessions, which is more comprehensive than traditional approaches such as TRIMP scores or intensity distributions after binning into training zones. These 2D KDE plots inform coaches in more detail on the internal and external training load of their prescribed training sessions and may help them design better training schemes aiming at desired training adaptations.

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