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Quantifying change of direction load using positional data from small-sided games in soccer

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ABSTRACT

Rapid changes in velocity and direction place high mechanical loads on players, but are ignored in commonly used load indicators.

Purpose: Quantifying change of direction (COD) load through positional data from small-sided games (SSG) and assess its criterion and construct validity.

Methods: Elite male youth soccer players (n = 25, 16.8 ± 1.3 years) played three SSG (5v5, 5×4 min) with different field dimensions (small [40×30 m], medium [55×38 m], large [70×45 m]). Positional data of the players was obtained with a Local Position Measurement system. COD load (AU) was quantified based on the combination of velocity and change in heading direction. Additionally, total distance covered, running distance, acceleration count, deceleration count, and Rating of Perceived Exertion were measured. Criterion validity was assessed by correlating COD load and the load indicators. Construct validity was determined by testing the differences between the SSG field dimensions.

Results: Strong correlations were determined between COD load and total distance covered ($r = 0.74$, $p < .01$) and running distance ($r = 0.84$, $p < .01$). Middle and large field size resulted in highest COD load ($p < .05$).

Conclusion: These results suggest that the COD load measure shows sufficient criterion and construct validity.

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KEYWORDS
Agility; load; small-sided games; local positioning

Introduction

In soccer, rapid changes in velocity and direction in response to a stimulus are considered key aspects of the game (Bloomfield et al. 2007; Faude et al. 2012). This is also known as agility and requires training to improve it. However, velocity in combination with changes of direction place high mechanical load on lower extremities (Besier et al. 2001), which can result in increased injury risk if this is poorly managed over time (Brent Edwards 2018). It is therefore of utmost importance to carefully plan and monitor the load associated with the ability of changing direction at high velocity (Sheppard and Young 2006; Jaspers et al. 2018; Harper and Kiely 2018).

To quantify training load, a distinction between external and internal training load is suggested (Impellizzeri et al. 2005). External load measures (e.g. total distance and distance covered in different speed zones) refer to the volume and the intensity of a training program. Internal training load measures (e.g. heart rate and Rating of Perceived Exertion [RPE]) refer to the physiological stress imposed on athletes (Impellizzeri et al. 2005). During changes of direction (COD) there is an increase in biomechanical load when compared to straight-line running (>14.4 km h^{-1}), due to the propulsive and braking forces associated with changing direction (Besier et al. 2001; Vanrenterghem et al. 2017; Verheul et al. 2020). While the first acceleration phase of CODs is comparable to straight-line running, CODs require eccentric muscle work of the lower extremities and a lateral/anterior placement of the foot to decelerate the body (Jones et al. 2016). Concentric muscle work, together with the elastic energy stored during the braking phase, is thereafter needed to accelerate the body in a new direction (Spiteri et al. 2013). Since current physical load indicators do not aim to measure this specific component, there is a lack of biomechanical load indicators (Verheul et al. 2020). This results in a likely underestimation of the external load of the athletes.

Validation of new load indicators has often been performed by testing its criterion and construct validity. Criterion validity, of for example RPE, was determined by correlating this measure with heart rate (Impellizzeri et al. 2004; Haddad et al. 2017). Likewise, PlayerLoad™ was tested by assessing the relationship between PlayerLoad™ and distance covered (in different speed zones) (Casamichana et al. 2013; Polglaze et al. 2015). An alternative method for validating load indicators, is changing the field size of small-sided games (SSG) (Hodgson et al. 2014). Since changing pitch dimensions influences the physical demands of a game (Casamichana and Castellano 2010; Hodgson et al. 2014), it is expected that the load variables react according to these changes. A larger field size results in more distance covered (at high intensities), higher maximum velocities and higher sprint frequencies (Casamichana and Castellano 2010). In contrast, smaller field sizes have an increased technical demand (more dribbling, turning and intercepting) (Casamichana and Castellano 2010; Hodgson et al. 2014). These characteristics suggest that changing field sizes can be used to determine the construct validity of a new physical load indicator.

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In Australian football, the number of COD actions increased with smaller field dimensions of SSG (Davies et al. 2013). Changes of direction were measured with notational analysis, because Global Position System (GPS) devices with sampling frequencies up to 10 Hz were not able to capture brief high-intensity activities (Jennings et al. 2010; Varley et al. 2012; Hodgson et al. 2014). Capturing these high-intensity movements requires information on velocity and heading changes (i.e. changes in the direction of instantaneous motion with respect to the pitch coordinates system), which can be derived from positional data (Varley et al. 2012). Modern-day positional tracking sensor technologies with higher sampling frequencies (25–40 Hz) allow for more accurate measurements of these activities. As agility is the ability to change velocity and/or direction in response to a stimulus (Sheppard and Young 2006), the interaction between velocity and heading changes can be used to measure this component with tracking sensor technology. However, since we do not measure the reactive component of agility with positional tracking technologies, it is only possible to measure the physical component of agility: COD load.

Even though it is known that changes of direction place a high mechanical load on athletes, current external load measures do not incorporate heading changes. Hence, the aim of this study is to develop a method to quantify COD load by means of tracking sensor technology and to determine its criterion and construct validity during SSG. Since COD are seen as high-intensity movements, correlations between high-intensity activities and COD load are expected. However, perfect correlations are not likely since we assume that COD load captures a unique aspect of training. In addition, it is expected that a larger field size results in higher COD demands of SSG, since larger field sizes allow higher velocities at which players need to turn.

Methods

Participants

Twenty-five elite male youth soccer players (16.8 ± 1.3 years, 179 ± 7 cm, 70.4 ± 7.8 kg) of the under-19 and under-17 teams of a professional soccer club in the Netherlands participated in this study (who trained 4 days a week). For each team, three training sessions were monitored in the winter of the 2016/2017 season. All participants provided written informed consent. If they were younger than 18 years old, both the players and their parents provided written informed consent. The procedures of this study were approved by the ethics committee of the Department of Human Movement Sciences, University Medical Center Groningen (UMCG), University of Groningen, the Netherlands.

Protocol

In this study, five 5 vs 5 SSGs were played on three different pitch sizes: a large pitch (70 by 45 m; 315 m^2 per player), a middle-sized pitch (55 by 38 m; 209 m^2 per player), and a small pitch (40 by 30 m; 120 m^2 per player). Players completed a standardized warming up prior to the SSGs. The duration of the standardized warming up was 20 minutes and consisted of: jogging, plyometric exercises, short sprints (10 m) and submaximal long sprints (40 m). Plays were divided into five 4-min periods, interspersed with 4 min rest. Official match rules were applied. Of the 25 available players, seven players participated in all three measurements, eight players took part in two measurements and 10 players were involved in a single measurement. Sixteen players were involved in measurements on the large and middle field size, and 15 for the small field.

Data collection

The local position measurement (LPM) system (Inmotio Object Tracking BV, Amsterdam, the Netherlands) was used to collect position data of the players at a sample rate of 40 Hz. Players wore a vest with one antenna on each shoulder that was connected to a transponder on their back. The technical aspects of the system, and the validity of LPM data are described elsewhere (Frencken et al. 2010).

Data analysis

Custom made software in Matlab (version 2018a; MathWorks Inc., Natick, Massachusetts, USA) was used to process the position data. Four parameters were calculated to represent the external load of players: (i) the total distance covered (ii) the total distance covered at running velocity (>14.4 km h^{-1}), (iii) the number of accelerations (velocity >2 m s^{-1} and acceleration >for at least 100 ms) (Gaudino et al. 2014; Stevens et al. 2014), and (iv) the number of decelerations (velocity >2 m s^{-1}, acceleration <−2 m s^{-2} for at least 100 ms) (Gaudino et al. 2014; Stevens et al. 2014). To account for possible differences in playing time between players, the number of accelerations and decelerations for each player was expressed as a percentage of total playing time. To quantify internal load, players rated their RPE scores on a 15-point Likert scale (ranging from 6 to 20) (Impellizzeri et al. 2004). RPE scores were collected a few minutes after the completion of the games.

Calculation of COD load

Previous research on COD has shown that movement velocity generally decreases with COD angle (Hader et al. 2015; Havens and Sigward 2015; Dos'Santos et al. 2018). Figure 1 illustrates that this relation is also a property of player movement on the pitch, showing the movement trajectory (Figure 1a), and the related velocity and heading change (i.e. the difference in horizontal heading angle between two consecutive points in time) data (Figure 1b) of a player for 100 s. Figure 1b demonstrates that, as sharper turns are made (i.e. the change in heading is large), player velocity is generally low, resulting in a negative correlation between both time series (r = −.455).

Figure 2 displays the relation between velocity and heading change for a typical player for a complete 20-min game. From this figure, it becomes apparent that the maximum attained velocity decreases with heading change. A second property of the velocity–heading change relationship that becomes clear from this figure, is that the maximum attained velocity decreases non-linearly with heading change. These two

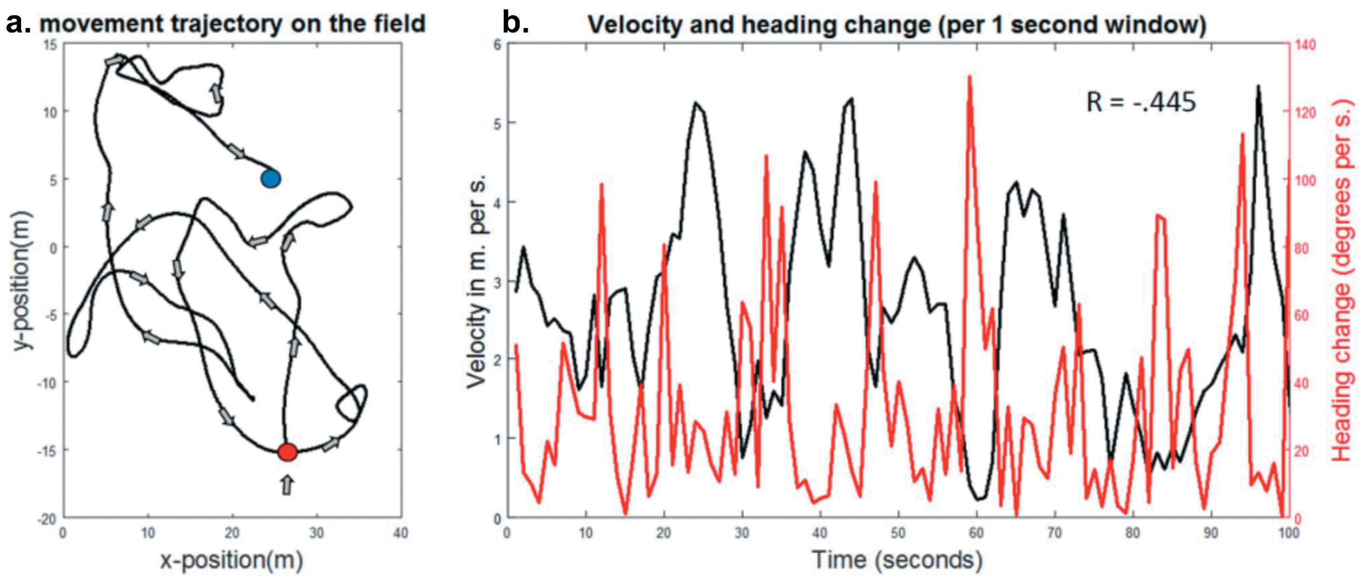

Figure 1. A. Movement trajectory (y is the length axis of the pitch) of a typical player for a period of 100 s. B. Velocity (black) and heading change (red) for the windowed data (1 s) displayed in figure 1A. The correlation between heading change and velocity for this epoch was −.445.

properties reflect the common intuition that at higher velocities, it becomes increasingly more difficult to make sharp turns. Because COD refers to the skill involved in changing heading at high velocities (Sheppard and Young 2006), we believe the features of the velocity–heading relationship described above, can be exploited to quantify COD load using position data obtained during real games.

For this purpose, we first selected time windows where agile action (i.e. substantial changes in heading at a relatively high velocity) occurred, based on a non-linear cutoff function that combines player velocity (m·s^{-1}) and heading change (degrees p. second), derived from position data (x, y) obtained by the LPM system. The heading angle ϕ was determined for each sample $t(1 \ldots n)$, as follows:

$$\phi_{(t)} = \tan^{-1}\left(\frac{\dot{y}(t)}{\dot{x}(t)}\right) \tag{1}$$

where $\dot{x}$ is the linear velocity in the x direction (i.e. the width of the pitch) and $\dot{y}$ is the linear velocity in the y direction (i.e. the length of the pitch). $\phi_{(t)}$ is positive for displacement to the right and negative for displacement to the left. Player velocity Vin the x–y plane was calculated for each sample t as

$$V(t) = \sqrt{\frac{(x(t) - x(t-1))^2 + (y(t) - y(t-1))^2}{dt}}. \tag{2}$$

To quantify the change in heading over time, time windows were defined. To this end, $\phi_{(t)}$ and $V(t)$ were segmented into m discrete time windows $w(1)$. Here, the duration of w was set to 1 s, assuming that meaningful changes in heading can be made within 1 s. The change in heading ($\Delta\Phi(w)$) was determined as the total change in $\phi_{(t)}$ within each time window w (i.e. the change in heading direction during 1 s). $\Delta\phi_t(w)$ is positive for turns to the right and negative for turns to the left. Player velocity within each window (V_w) was calculated as the average velocity $V(t)$ within time window w (i.e. the average velocity of all measurement during 1 s).

As becomes clear from Figure 1b, players predominantly move at lower velocities, and/or travel straight trajectories, so that the player's COD-related skills are hardly addressed. Therefore, to determine the COD load, we chose to restrict the analysis to selected time windows in which a minimum velocity and a minimum direction change were displayed. In accordance with the properties of COD outlined above (i.e. a non-linear decrease in velocity with increasing curvature), the following function was defined as a velocity and curvature dependent cutoff:

$$\frac{1}{k * \Delta\phi(w)}. \tag{3}$$

As Figure 2c illustrates, the shape of the cutoff function can be tuned to some extent by adjusting k. Based on visual inspection of the data, for the present purpose k was set to 0.15. The resulting cutoff curve is plotted in Figure 2a. Data above the curve (black dots) were included, whereas data below the curve (gray dots) were excluded for determining the COD load. Based on the assumption that for a given angle, a higher displayed velocity corresponds to a greater COD load, the COD load $A(w)$ was calculated for each window w as the vertical distance to the cutoff curve, as follows:

$$A(w) = V(w) - \frac{1}{k * \Delta\phi(w)}. \tag{4}$$

Finally, for each player n, the average COD load $\bar{A}(n)$ over the measurement period was calculated in arbitrary units as

$$\bar{A}(n) = \frac{\sum_{w=1}^{m} A(w)}{m}. \tag{5}$$

The individual COD load scores were then used for statistical analysis.

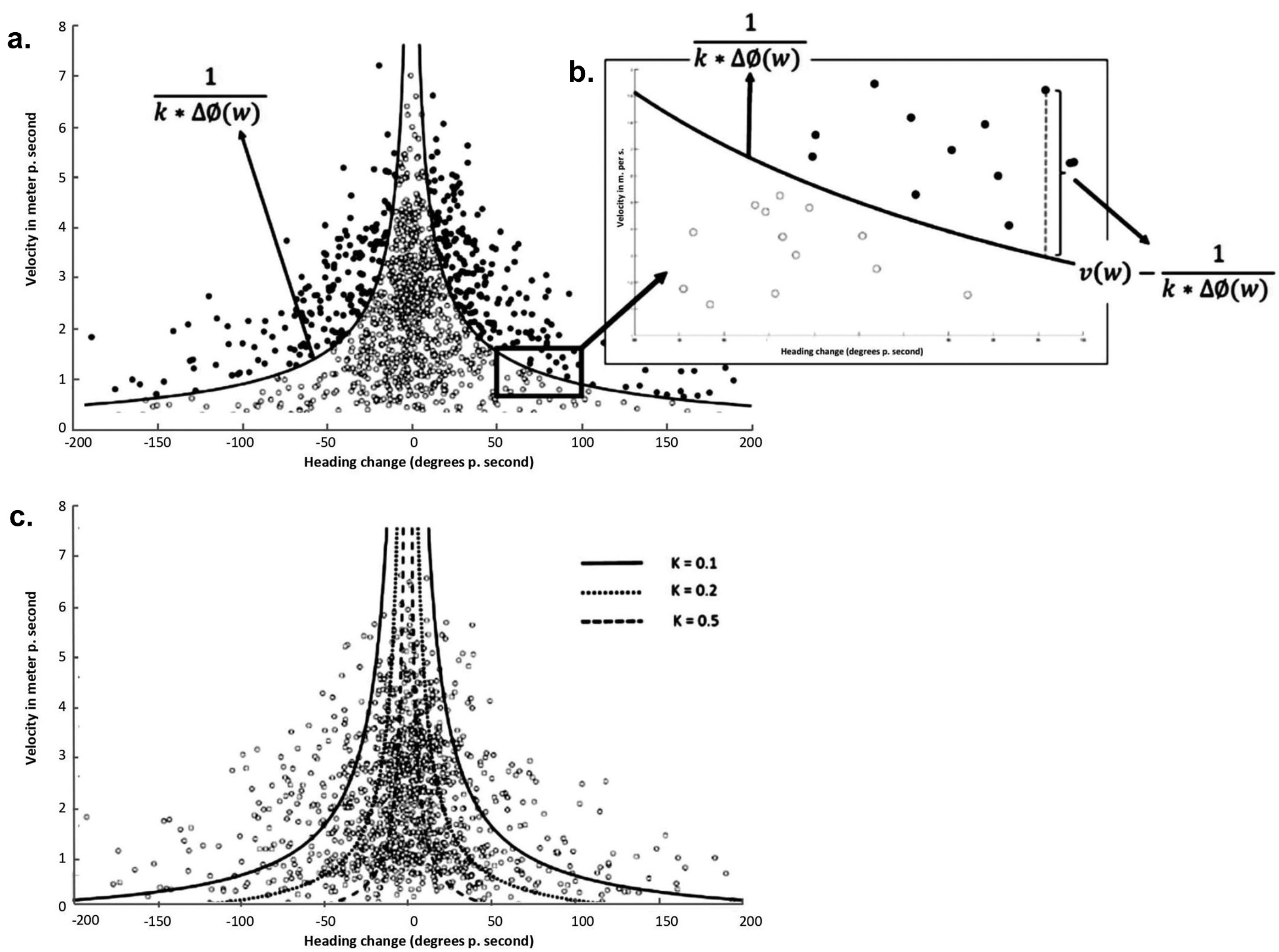

Figure 2. Calculation of the COD load parameter. (A) Combined velocity (vertical axes) and heading change (horizontal axes) data for a single player for all 1-s windows during a complete 20-minute match (70 by 45 m pitch, rests excluded). Each dot represents a 1-s time window. If the average velocity within a given window was higher than $1/(\kappa \times \Delta\varphi(\omega))$ (where $\Delta\varphi$ represents the observed heading change within the time window), data from this time window were included (black dots). Data below the cutoff function were not included in calculation of the COD load analysis (gray dots). (B) Detail of (A) illustrating the calculation of the COD load $A(\omega)$ for each window ω as the vertical distance to the cutoff curve $1/(\kappa^* \Delta\varphi(\omega))$. (C) Tuning of the cutoff function by using different values of κ.

Statistical analysis

Criterion validity was determined calculating the Pearson correlation between the COD parameter and each of the external load parameters (total distance covered, distance covered at high velocity, number of accelerations, number of decelerations), and internal load parameter (RPE scores). To simplify the analysis, only the data obtained on the large pitch (n = 16) were included in this analysis as this most closely resembles the dimensions of a normal soccer pitch. In accordance with Cohen (1988), relations with correlations of .1 were considered weak, .3 were considered moderate, and .5 were considered strong.

To test the construct validity of the COD parameter, a linear mixed model (LMM) was set up to evaluate the effect of field size (small, middle, and large) on COD load and the other load indicators. A LLM was used because the number of repeated measures (i.e. number of times each participant participated in a trial), differed between participants. For this analysis, field size was used as first level of analysis and individual athletes represented the second level of analysis. Since a repeated measures design was chosen, data could be analyzed with a compound symmetry matrix. Because the assumption of equal variances and covariances was violated, an unstructured matrix was used for analysis. In case of significant main effects of field size, post hoc pairwise comparisons were conducted to analyze differences between different field sizes. Bonferroni corrections were applied to maintain the familywise error rate at 5%. Furthermore, effect sizes (ES) were calculated for the paired comparisons. All statistical analysis was done using SPSS version 23.0 (SPSS Inc., Chicago, IL, USA).

Results

Results of the correlational analysis revealed a strong relationship between COD load and total distance covered (r = 0.74, p < 0.01), and running distance (r = 0.84, p < 0.01). No significant relationship was found between COD load and the

Table 1. Average values (+standard error) for the load indicators.

	COD load	Total distance covered (m)	Running distance covered (m)	Number of accelerations as percentage of time (%)	Number of decelerations aspercentage of time (%)	RPE (AU)
Large	.31 (0.05)*	3300 (40)*	929 (24)*#	.076 (.002)	.071 (.002)	17.47 (.33)
Middle	.33 (0.04)*	2890 (30)	803 (33)*	.080 (.002)	.078 (.002)	17.83 (.18)
Small	.22 (0.06)	2710 (140)	494 (26)	.083 (.005)	.079 (.004)	17.37 (.34)

*Significantly different from small field size.
#Significantly different from middle field size.

number of accelerations (r = .18), the number of decelerations (r = −.01), and RPE scores (r = .12; $p > 0.05$ for all comparisons).

The average values for COD load and the load parameters are shown in Table 1. Results from LMM showed that COD load differed between field sizes ($F(2,7.22) = 53.48$; $p < 0.001$). Post hoc analysis showed that the average COD load was significantly lower for the small field size (0.22 ± .06) compared to the middle-sized (0.33 ± .04; $p < 0.001$, ES = 2.21) and large field (0.31 ± .05; $p < 0.001$, ES = 1.84).

Total distance covered also differed between field sizes ($F(2,13.43) = 27.17$; $p < 0.001$), with significantly larger distances observed on the large field (3300 ± 40 m) compared to the middle-sized (2890 ± 30 m; $p < 0.001$, ES = 2.27) and the small field (2710 ± 140 m; $p < 0.05$, ES = 1.12). Likewise, running distance (>14.4 km h^{-1}) differed between field sizes ($F(2,12.23) = 331.94$; $p < 0.001$). Players running distances were higher on the large field (929 ± 24 m) compared to the middle-sized (803 ± 33 m; $p < 0.05$, ES = 0.86) and the small field (494 ± 26 m; $p < 0.001$, ES = 3.33). Running distance also differed significantly between the middle-sized and the small field ($p < 0.001$). The number of accelerations ($F(2,12.51) = 1.58$), the number of decelerations ($F(2, 9.65) = 3.37$), and RPE ($F(2,14.88) = 1.73$) did not differ significantly between different field sizes ($p > 0.05$ for all comparisons).

Discussion

The aim of the present study was to quantify COD load with tracking sensor technology and assess its criterion and construct validity during SSG. To do so, a novel compound measure was developed that included both velocity and heading change. The main results of this study show that there were strong correlations between COD load and the total distance covered and running distance for the large field size. Weak non-significant relationships were found between COD load and the number of accelerations, the number of decelerations, and RPE scores. Middle and large field sizes resulted in highest agility load. Correlations between the commonly used physical load indicators and COD load ranged from weak non-significant correlations to strong significant correlations for the large field dimension. Strong significant correlations were present between COD load and total distance covered and running distance. Since COD load consists of both velocity and changes of direction, it is unsurprising that for the large field dimension, it relates to running distance. Logically, when more distance is covered at higher speed, this results in more distance covered and thus in a strong significant correlation with total distance covered as well.

A weak non-significant relationship was found between the COD parameter and the number of accelerations and decelerations. Whilst is might be surprising that COD load does not correlate with the number of accelerations and decelerations for the large field dimensions, it can be understood by the velocity-heading change trade-off (Dos'Santos et al. 2018). Accelerations and decelerations were counted based on predetermined thresholds and often occur at lower velocities when player initiate action (i.e. getting past an opponent) (Varley and Aughey 2013). Even though this will likely include changes of direction, only large heading changes at low velocities do markedly contribute to COD load, since these are thought to impose a higher biomechanical load (Dos'Santos et al. 2018). Therefore, even though these accelerations/decelerations may have included (small) heading changes, it did not markedly contribute to COD load. Finally, RPE was weak and non-significantly associated with COD load. Since RPE is known to be related to cardiovascular indicators (Impellizzeri et al. 2005), and COD load aims to capture biomechanical demands, lack of relation with RPE was to be expected.

Adjusting the field dimensions of SSG resulted in highest COD demands for the middle and large field dimension. This supports construct validity and coincided with increased total distance covered (at running speed) but also lower (although not significantly) number of accelerations and decelerations for larger field sizes. The middle-sized field tends to have even higher COD load compared to the largest field size. An explanation for this is that velocity is expected to be highest on a large field sizes but changes of direction on small field sizes. Since COD load combines both aspects, the finding is in line with the hypothesis and in accordance with previous research (Casamichana and Castellano 2010; Davies et al. 2013; Hodgson et al. 2014; Gaudino et al. 2014; Malone and Collins 2017).

It might be surprising that the number of accelerations and decelerations did not significantly differ between field sizes, giving the fact that other studies did find significantly different values between field sizes (Gaudino et al. 2014; Malone and Collins 2017). One of the explanations for this is that there were differences in how acceleration and decelerations efforts were defined (i.e. differences in time and velocity thresholds) between previous research and the current study. Next to this, threshold-based accelerations have been reported to have good-to-poor reliability, since small differences in the measured acceleration might lead to the same effort being registered or not (Thornton et al. 2016). Hence, a more robust acceleration measure (e.g. average acceleration) might have been able to measure differences between field sizes.

The unique responses of the other load indicators to changes in field sizes can be explained by the fact that these variables represent physiological or biomechanical loads (Vanrenterghem et al. 2017). The finding that internal load did not differ between different field dimensions might support this. Players could have perceived decreasing physiological loads corresponding to less distance covered at smaller field dimensions, but also higher biomechanical loads due to more decelerations and accelerations. Resulting in the same internal load, but with different contributions of the components. Indeed, players are able to recognize the different feelings of breathlessness, muscle exertion, and cognitive exertion corresponding to different training exercises and matches (Weston et al. 2015; McLaren et al. 2016, 2017). Based on the current results we cannot draw any conclusions on whether the internal load for the three SSGs is composed in different ways, even though the external load measure do suggest this might be the case.

To better understand the training process, a distinction between the physiological and biomechanical load has been proposed (Vanrenterghem et al. 2017). An indication of the physiological load on the body can be retrieved from variables such as the distances covered in different speed zones (Vanrenterghem et al. 2017). When the physiological system is sufficiently stressed during training, positive metabolic and cardiorespiratory adaptations take place. On the other hand, physical load also incorporates a biomechanical component. Propulsive and braking forces associated with changes in velocity and/or direction place high loads on soft tissues (Harper and Kiely 2018; Verheul et al. 2020). When these biomechanical aspects are adequately managed over time, positive adaptations occur (e.g. changes in tendon structure and stiffness) (Verheul et al. 2020). To ensure that positive adaptations take place in response to both types of stressors, it is needed to get an indication of the physiological and biomechanical load over time. Even though the physiological load is well represented in the current physical load variables, the biomechanical load is largely overlooked.

Although there is a growing understanding that biomechanical load should be measured separately, there have been difficulties in estimating the biomechanical load in practice. Motion-capture systems and force platforms are currently used to indirectly estimate the load acting on tissues (Verheul et al. 2020). However, these methods are restricted to laboratories and are therefore not suited for daily practice. Inertial measurement units (IMU) fixed to lower body extremities may be able to measure joint kinematic in team sport practice, and might overcome low ecological validity of lab testing (Cuesta-Vargas et al. 2010). Recent research has shown promising results for measuring joint kinematics with IMUs for linear sprinting (Bastiaansen et al. 2020) and football-specific movements (Wilmes et al. 2020). However, there remain difficulties with the application in games due to the displacement of the sensors when making tackles (i.e. it might bruise players and it hinders the measurement) (Bastiaansen et al. 2020; Wilmes et al. 2020). The smart sensor shorts, which aim to overcome displacement of sensors, need further development in future. In the meantime, we propose the current COD load variable as good alternative to get an indication of the biomechanical load on the players in team sport practice.

This study is the first to quantify COD load of SSG with time-motion analysis by using the interaction between velocity and heading changes. By using tracking sensor technologies with a high sampling frequency, it was possible to accurately measure high-intensity activities. A limitation of the current study is that we could not fully control the formations of the teams for each SSG, due to some injuries and illnesses. As a consequence, the teams slightly changed between the conditions. Therefore, differences between the field dimensions might be bigger or smaller than shown in this study. However, missing data was handled well with the use of mixed linear models. Future research could focus on the relation between COD load and relevant training outcomes such as performance. In addition, the role of COD load as risk factor for injuries could be assessed. Furthermore, one could also assess the COD parameter as performance outcome and a replacement for field testing. A major advantage of this approach is that it can be transferred to other team sports and overcomes poor specificity of general tests (Brink and Lemmink 2018).

Conclusion

To summarize, COD load is strongly correlated with total distance covered and the running distance covered during large-sized SSG in young elite soccer players. This supports criterion validity. The different patterns for the distances covered and COD demands of SSG with changing field sizes, show that the COD variable has sufficient construct validity.

Disclosure of interest

All authors have no conflict of interest and declare that the results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation.

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