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Application of a continuous pressure metric for Australian football

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Application of a continuous pressure metric for Australian football

Ben Teune [a,b], Bartholomew Spencer [a], Alice J Sweeting [a,b], Carl Woods [a], Mathew Inness [a,b] and Sam Robertson [a]

[a]Institute for Health and Sport, Victoria University, Melbourne, Australia; [b]Football Department, Western Bulldogs, Melbourne, Australia

ABSTRACT

Pressure is an important constraint on sports performance and is typically measured through manual notational analysis. A continuous representation of pressure, along with semi-automated measurement, would serve to improve the efficiency of practice design and analysis, as well as provide additional context to player competition performance. Using spatiotemporal data collected from wearable tracking devices, the present study applied Kernel Density Estimation to estimate the density of players, relative to the ball carrier, at point of skill execution during elite Australian Football training. Two environmental constraints were measured (*area per player* and *number of players*) to determine the relationship between these training design manipulations and density. Density was also compared with existing notational analysis measurements of pressure. Results indicated that a higher density on skills was associated with successful skill executions. The opposite relationship was found between notational analysis pressure measurement and skill effectiveness. A strong inverse relationship was found between environmental constraint manipulation and density, whereby increasing field size and playing number decreased the density on skill involvements. The findings offer insight into the continuous measurement of pressure and encourage practitioners to utilize training design manipulations to influence density as a constraint on skills.

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KEYWORDS
Density; constraints; manipulation; training design; team sport; skill

Introduction

The constraints-led approach (CLA) is a theoretical framework that situates movement as an adaptive property of the performer-environment system (Davids et al., 2008). Constraints act internally and externally to an individual, interacting and changing over time to shape movement and behaviour (Newell, 1986). It is therefore critical, that constraints be measured with sufficient detail and accuracy to gain insight into *how* and *why* particular movements and behaviours emerge (Glazier, 2017; McGarry, 2009). For sport practitioners, the measurement of constraints that shape the behaviour of athletes would likely provide important contextual information for evaluating player behaviour and designing learning environments intended to develop skill (Davids, 2012; Woods et al., 2020). To this end, improving the implementation of the CLA in sport can be achieved through: i) the measurement and consideration of additional constraints, ii) the application of enhanced analytical techniques or, as in the current study, iii) the improved measurement of an existing constraint.

In team sports, a commonly measured constraint is pressure, which is typically defined as the presence of opposition players in a nearby location at the time of skill execution (Andrienko et al., 2017). Given this definition, it is often used interchangeably with density (Link et al., 2016). A common method to measure pressure is to subjectively assign levels (e.g. low, medium and high) via notational analysis, according to the distance between an attacker and the nearest defender during skill execution. This has been applied in basketball (Csataljay et al., 2013) and field hockey (Timmerman et al., 2017, 2019). During futsal shots on goal, the distance of defending players to ball trajectory has also been used as an indicator of pressure (Vilar et al., 2013). In soccer, other methods have utilized spatiotemporal data derived from Global Positioning Systems (GPS), such as distance, velocity, and direction of players, to develop numerical measures for pressure (Andrienko et al., 2017; Link et al., 2016). The majority of pressure metrics have focused on physical pressure, but other construct definitions of pressure have also been reported in the literature. These include situations incentivizing optimal or maximal performance (Baumeister & Showers, 1986), which can manifest through increases in anxiety or emotional responses and thus may negatively impact skill performance (Eysenck, 2013).

In Australian Football (AF), the quantification of pressure has been represented in multiple ways. Types of pressure have been allocated to a skill execution according to the location of defending players, for example, side, frontal, chase or physical (Browne et al., 2019; Ireland et al., 2019; Robertson et al., 2019), along with the number of players within a 3 m boundary to the ball carrier (Woods et al., 2019). Opposition presence around pass receivers has also been recorded as a means of capturing indirect pressure on the passer and direct pressure on the receiver (Browne et al., 2019; Ireland et al., 2019; Woods et al., 2019). Some evidence exists to support the validity of pressure being measured in these ways, specifically due to the association with unsuccessful kicks (between 14.6% and 38.5% efficiency) during AF match play (Browne et al., 2019).

As spatiotemporal data pertaining to players is available in elite AF (with the exclusion of opposition data) there are opportunities to utilize it to improve the sophistication of existing pressure measurements. Thus, a measure of player density was

CONTACT Ben Teune benteune@outlook.com Institute for Health and Sport, Victoria University, Melbourne, Australia

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recently developed by applying Gaussian mixture modelling to spatiotemporal datasets during match play (Spencer et al., 2017). This method captured the interaction of all players on the field simultaneously. The work highlighted the changing congestion of players throughout a match, revealing that successful possession chains have large changes in density (Spencer et al., 2017). An adaptation of this type of analysis may provide a valuable metric to improve upon the current measures of pressure by providing a continuous metric. It may also facilitate consideration of the influence of players not within the immediate vicinity of the ball carrier.

The present study seeks to adapt the methodology of Spencer et al. (2017) to use density estimation as a proxy for pressure in AF. The first aim was to determine the extent of the relationship between pressure and the effectiveness of skill involvements. The second aim was to determine the extent to which environmental constraints, as part of training design, influence the pressure on skill execution during training drills. A third aim was to compare pressure derived from density estimation with pressure derived from notational analysis. Establishing these relationships may inform how pressure can be utilized in practice design, while providing additional context to player competition performance.

Methodology

Participants

Participants were listed male players from a single professional AF club (n = 43, 24.2 ± 3.5 y, 186.8 ± 7.7 cm, 84 ± 7.8 kg). All players provided written informed consent and were injury free at the time of participation. Ethical approval was obtained from the relevant University Ethics Committee.

Data collection

Data were collected during the 2020 Australian Football League pre-season. A total of 32 training activities were selected for analysis, consisting of eight different drills and 1014 skill involvements (72% handballs and 28% kicks). Drills that were selected were characterized as small sided games (by the club's coaching staff) and consisted of two opposing teams with equal numbers. Team selection was quasi-randomized by the clubs coaching staff to standardize skill level and player experience. The objectives of each drill were nuanced, they generally required teams to score by kicking a goal or completing a pass into a zone at one end of the field. Further, the drills covered all aspects of AF including ball movement, decision making, offensive and defensive actions. Drills ranged from 46.88 m^2 per player to 570 m^2 per player and the total number of players ranged from eight to 20.

To obtain records of each skill involvement, drills were filmed with a two-dimensional camera from either a side-on or behind-the-goals perspective. Cameras were situated in a fixed position and vision angle varied depending on location of the drill at the time of performance. To quantify skill involvements and the surrounding task constraints, notational analysis software was used (Sportscode, version 12.2.10, Hudl). A custom code window was created whereby each skill involvement was recorded live, during the session, according to the method (kick or handball) and the outcome (effective or ineffective). Disposal outcome was defined in accordance with Champion Data (Melbourne, Pty Ltd), the commercial statistics provider for the Australian Football League. A handball or kick less than 40 m was deemed effective if the intended target retained possession of the ball. A kick greater than 40 m was deemed effective if kicked to a 50/50 contest or better for the attacking team. Post training, the Sportscode window was used to attribute additional, notational analysis labels to each skill involvement, according to the type of pressure present. Pressure was categorized into four levels; None, Frontal, Chase and Physical (Robertson et al., 2019). These levels were also used to determine a binary pressure measurement by combining Frontal, Chase and Physical into "Present" and using None as "Absent". Coders followed club procedure on "what to look for" when performing notational analysis to ensure consistent interpretations. To assess the intra-rater reliability of the skill involvement coding, three activities consisting of 145 involvements were coded on two separate occasions with at least 14 days between. The Kappa statistic (Landis & Koch, 1977) was used to assess intra-rater reliability of effectiveness and pressure. Agreement was "almost perfect" for effectiveness (0.93) and binary pressure (0.83) and "substantial" for pressure (0.79). All skill involvement data was exported, according to their drill, into a custom Microsoft Excel spreadsheet.

Spatiotemporal data for each player was collected with 10 Hz GPS units (Vector S7, Catapult, Catapult Sports Ltd, Melbourne). Devices were placed in a vest in a custom pouch between the athlete's shoulder blades prior to the session beginning. Players wore the same device during each session to reduce inter-unit error. During the session, splits were created marking the beginning and end of each activity in the manufacturer's software package (*Openfield*, version 2.5.0). To create a reference point to join skill data with spatiotemporal data, a start label was also coded in Sportscode at the start time of each drill. After session completion, raw spatiotemporal data was exported from *Openfield* into Microsoft Excel for each player and for each training activity. To differentiate teammate and opposition locations, using the recorded footage, each player's spatiotemporal data were arbitrarily assigned a team label for each training activity.

To determine player location for each skill involvement, exported spatiotemporal data and skill involvement data were joined according to their timestamp for each training activity. For both datasets, timestamps were adjusted relative to the beginning of each activity. Latitude and longitude for each player was converted to x and y coordinates, in metres, relative to the ball-carrier position which was set at 0,0. Using assigned teams, each player location was labelled as opposition or teammate, relative to the player performing each skill involvement. Kernel density estimation, a method of estimating the probability density function of a dataset via smoothing of individual points, was used to estimate the density of players at each skill involvement (Simonoff, 1996). The kernel function and bandwidth dictate the shape and smoothness of the resultant probability density function, respectively. Density was estimated using Gaussian kernels and the bandwidth was arbitrarily set to 0.00006 for all samples. A visual example of a sample is presented in Figure 1. Density was calculated across two groups; all players and opposition players only.

To measure constraint manipulation with respect to training design, two environmental constraints were recorded for each training activity. The constraints selected were *area per player* and total *number of players*, which have shown relationships with player density (Silva et al., 2015; Timmerman et al., 2017). Number of players was defined as the total number of players participating in the drill. The area per player was defined as the total playing area of the field, as designated by markers and manually measured before each activity, divided by the number of players. All constraint manipulations for each training activity were recorded and databased in a custom Microsoft Excel™ spreadsheet.

Statistical analysis

All statistical analyses were performed in R (version 3.6.1, Vienna, Austria)using base R functions. Density estimation scores were normalized to the mean, as *z* scores, for both groups: all players and opposition players. To address the first aim, logistic regression models were constructed to determine the relationship between density and skill effectiveness (effective or ineffective). Visual inspection of the distribution of density revealed no substantial differences when considered as only defending players or all players from both teams combined. Consequentially, the remainder of the analysis considered all players from both teams. Three models were constructed; considering either i) only handballs, ii) only kicks or iii) all skill involvements. To address the second aim, a multiple linear regression model was constructed to determine the relationship between the two manipulated environmental constraints (area per player and number of players) and density. To address the final aim, two logistic regression models were constructed to determine the relationship between i) notational analysis pressure according to location and ii) notational analysis pressure as binary (present or absent) and skill effectiveness (effective or ineffective).

Results

For the entire dataset, 83.2% of involvements were effective. Density scores for each involvement were a normalized value, where mean = 0 and SD = 1 and where a higher value represents more density on the skill involvement and vice versa. A visualization of the distribution of density for the entire sample is provided in Figure 2. Logistic regression analysis revealed that for handballs only (B = −0.04, z = −0.334) and for kicks only (B = 0.347, z = 0.976), there was a very weak positive relationship between density and effectiveness. Across all skill involvements, logistic regression analysis revealed that density and effectiveness were positively associated (Model 1 in Table 1). This indicates when density was higher, it was more likely for an effective disposal to occur; however, the association was weak (z = 2.437). Mean density for effective disposals was 0.034 SD and mean density for ineffective disposals was −0.171 SD.

To address the second aim, 32 training drills were analysed. Descriptive statistics are reported as a mean and standard deviation. The mean number of involvements was 31.7 ± 12.2, the mean disposals per minute was 9.9 ± 4.3, the mean number of players was 11.6 ± 3.5 and the mean area per player was 176.9 m^2 ± 165.2 m^2 per drill. Results of the multiple linear

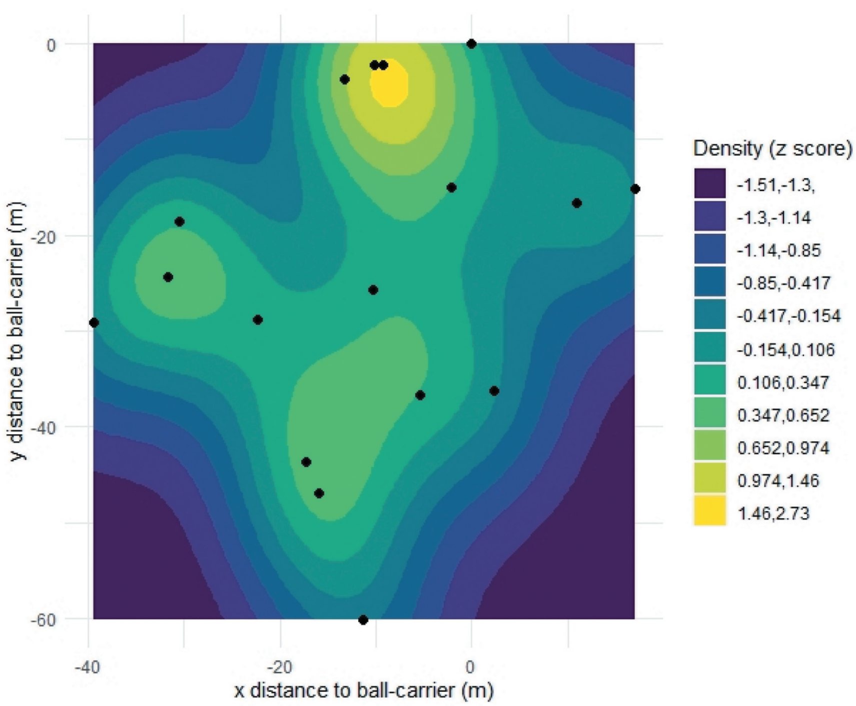

Figure 1. Example representation of a single skill involvement. Points represent player positioning relative to the ball-carrier which is at 0,0. Contours and colour represent density (z score), with positive values indicating higher density.

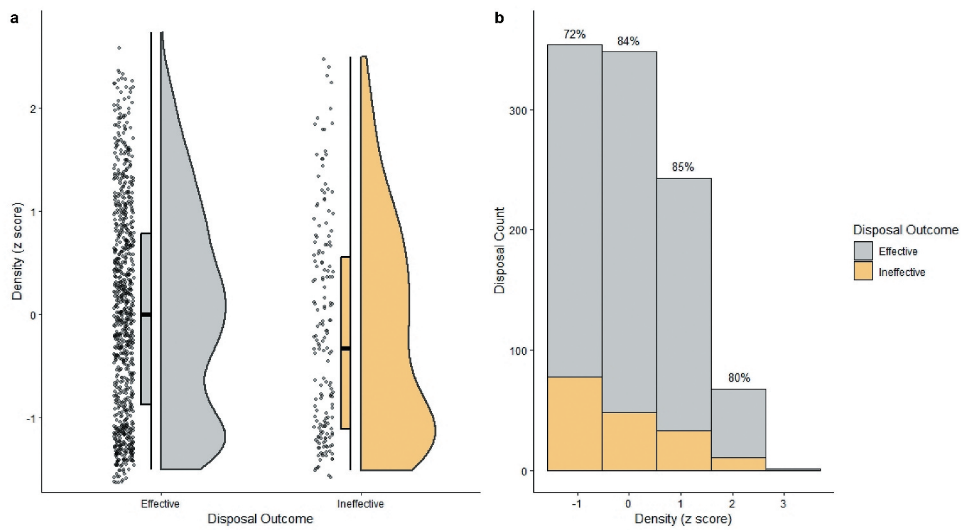

Figure 2. Distribution of density for effective and ineffective skill involvements. A: Each dot represents a single skill involvement. Box and whisker plots indicate the median, interquartile range, minimum and maximum values. Half violin plots represent a continuous distribution of density. B: Histogram bars are stacked according to disposal effectiveness with labels above each bin representing disposal effectiveness (%).

Table 1. Results of logistic regression models. Model 1 shows the relationship between density and skill effectiveness. Model 2 shows the relationship between each level of pressure measured through notational analysis and skill effectiveness. Model 3 shows the relationship between pressure as a binary notational analysis measurement and skill effectiveness. Coefficient and test statistic (z) presented for each variable.

	Effectiveness		
	Model 1	*Model 2*	*Model 3*
Density	0.212* z = 2.437		
Notational Pressure: Chase[a]		−0.328 z = −1.212	
Notational Pressure: Frontal[a]		−0.366 z = −1.798	
Notational Pressure: Physical[a]		−1.147*** z = −4.315	
Notational Pressure: Binary[a]			−0.523** z = −3.089
(Intercept)	1.617*** z = 18.987	1.858*** z = 14.969	1.858*** z = 14.969
Akaike Inf. Crit.	914.858	906.45	910.594

*p < 0.05, **p < 0.01, ***p < 0.001
[a]Notational Pressure: "None" used as reference category

regression analysis are shown in Table 2. Overall, the model explained 54% of the variance in density. Area per player and number of players each showed a significant inverse relationship with density, with area per player ($t = -15.427$) showing a slightly greater effect than number of players ($t = -13.612$). This indicated that as area per player and number of players increased, density on skill involvements was more likely to decrease (Figure 3).

Table 2. Results of the multiple regression analysis estimating the relationship between manipulated environmental constraints (area per player and number of players) and density. Coefficient (*B*) and test statistic (*t*) presented for each variable. *p < 0.01.

	Density	
	B	*t*
Area per Player	−0.003*	−15.427
Number of Players	−0.099*	−13.612
Constant	1.729*	22.969
Adjusted R^2	0.543	

Across all skill involvements the proportion of each level of the pressure constraint represented in the data was; No Pressure = 55%, Physical = 8%, Frontal = 25%, Chase = 12%. To address the third aim, results of the two logistic regression models are shown in Table 1 (Models 2 and 3). Using No Pressure as the reference category, only Physical pressure was shown to have a weak relationship with skill effectiveness ($z = -4.315$), reducing the likelihood of an effective skill involvement (Model 2). When notational analysis pressure was made a binary variable, a significant inverse relationship with skill effectiveness is shown (Model 3). This indicated that a skill involvement performed under the constraint of pressure, regardless of location, was more likely to be ineffective than effective; however, this association was weak ($z = -3.089$).

Discussion

The overarching objective of this study was to apply a continuous density metric to represent the constraint of pressure in AF. To achieve this, the first aim examined the relationship between density and skill effectiveness, which revealed that density had a weak, positive association with disposal effectiveness. This was contrary to expectation, as in other spatiotemporal derived methods for pressure measurement, pressure is seen as increasing when distance to a defender decreases (Andrienko et al., 2017; Link et al., 2016). However, unlike in other studies (i.e. Andrienko et al., 2017; Link et al., 2016), the present study's metric is the measurement of displacement for *all* players on the field, relative to the ball carrier. This suggests that this type of measurement presents differently to measurements which only value opposition players within an immediate vicinity. Multiple explanations are offered for this. Firstly, lower density levels around the ball carrier can indicate a wide spread of players across the playing field. This suggests that defending players are well

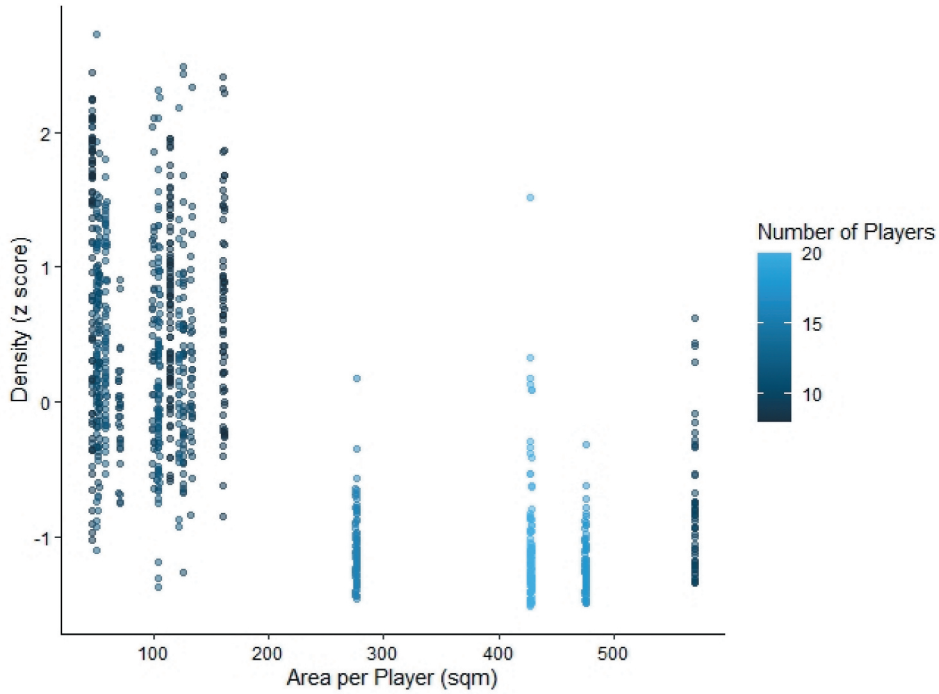

Figure 3. Relationship between environmental constraints (area per player and number of players) and density. Each point represents a skill involvement.

placed to cover large portions of the field, increasing the difficulty on the ball carrier in finding open space around a passing target. Indeed, in AF there is a tendency for players to favour targets with lower density (Spencer et al., 2017). It may also be partially explained by the tactical constraints which shape decision-making by players (Pill, 2014). For example, it is a common tactic among AF players to "draw" opponents closer, creating open spaces around teammates before executing a pass. Therefore, increased density on the ball carrier is likely to be related to lower densities for passing targets, potentially increasing the likelihood for a successful pass. It should also be noted that in the current sample, 83.2% of involvements were effective which represents a higher efficiency than noted during the 2019 competition (71.5%; www.afl.com.au/stats). Thus, these models may infer different results in competition.

Pertaining to the second aim, the relationship between density and environmental constraints showed that both area per player and number of players were inversely associated with density, with area per player having a larger effect than number of players. To date, no work has measured this type of density under constraint manipulation, rather density has been measured as a collective team behaviour through total surface area of players during a training activity (Silva et al., 2015; Timmerman et al., 2017). Findings in the present study support results observed in soccer (Silva et al., 2015), and to some extent, in field hockey (Timmerman et al., 2017). In field hockey, density has been shown to be influenced by environmental constraints, whereby the number of players is more influential than area per player (Timmerman et al., 2017). In AF, pressure on the kicker, as measured through notational analysis, is not solely influenced by manipulating the number of players in a drill (Bonney et al., 2020). This differs to the current study's measure of pressure. However, notational pressure may not be sensitive enough for small constraint manipulations, such as in Bonney et al. (2020), to illicit change. The present study has shown that environmental constraints influence density, relative to the ball carrier, and it is encouraged that practitioners consider this in training design. When designing training, environmental constraints may be strategically manipulated to expose players to skill executions in specific densities, depending on the focus of the session.

The final aim compared pressure measured via notational analysis with the density-derived pressure metric. For the former method, only physical pressure showed a meaningful relationship with skill effectiveness. This was expected, as intuitively, skill performance under physical contact from an opponent would be more challenging than other forms of pressure. This is also in agreement with other work examining kicking in AF (Browne et al., 2019). However, when pressure was dichotomized as "present" (combining all categorizations of pressure) or "absent", a weak negative association was shown, meaning players were more likely to perform an unsuccessful pass when under pressure. This result contradicts the relationship found between density and skill performance. A potential explanation may be in the strict 3 m proximity, within which pressure was measured, through notational analysis. Unlike the density metric, no account is provided of player location beyond this vicinity. While originally hypothesized as a limitation, these results suggest this may be advantageous in understanding skill performance. Providing a value for the underlying distribution of players throughout an entire field may undermine the influence of defenders within the immediate vicinity of the ball carrier. For example, an unsuccessful pass which is measured as under pressure through notational analysis, may also measure low in density, due to the wide spread of players across the rest of the field. It may be concluded that density is not a replacement metric for pressure, as measured through notational analysis, but still contributes to understanding skill performance.

Practically, the results of this study show that density is inversely related to pressure. Consequently, more information may need to be considered in order to explain skill effectiveness more accurately. Specifically, including a measure of pressure or density surrounding targets would be advantageous to better understand the task constraints on skilled behaviour. It is clear that accurate modelling of skill performance requires the measurement of more than a single constraint (Browne et al., 2019; Lucey et al., 2014; Pocock et al., 2018; Vilar et al., 2013). Such multivariate analyses have shown how constraints including pass distance, locomotive velocity and time in possession influence kicking performance in AF (Browne et al., 2019).

The density metric used in this study also contains multiple limitations which should be noted. Notably, measuring player density via kernel density estimation does not reflect player velocity and orientation. Logically, players can apply more pressure to space they are travelling towards (Fernandez & Bornn, 2018). Additionally, whilst density considers the relative locations of opponents, outputting density as a continuous, numerical value does not convey information about the direction of pressure being applied to the passer. Traditionally, pressure is measured categorically in AF by recording the location of pressuring opponents to the player. For example, "chasing" pressure signifies opponents are applying pressure behind the player with possession (Browne et al., 2019; Ireland et al., 2019; Robertson et al., 2019). Future work should address these limitations through utilization of a measure of spatial occupancy that considers player velocity and orientation (e.g. Fernandez & Bornn, 2018; Spencer et al., 2018). Other limitations of the present study include the synchronization of spatiotemporal and skill event data, which carries inherent error due to a reliance on human communication to determine synchronization points, along with timing errors which may occur during event logging of skill data. Additionally, no inter-rater reliability analysis was conducted on skill data. Further, density was limited to a static measurement at the time point of skill executions. While this presents a method which is simple in application, density as a pressure metric may be suited to a measure which occurs over time, such as the seconds leading up to a skill execution or during the entire period of a player's ball possession. It is suggested that future work examine density as it is temporally distributed over such time periods. It is also important to note that density is limited to measurements in a two-dimensional plane; however, AF is a three-dimensional sport where player jumping ability and height may attenuate or increase pressure. Finally, the analysis in this study was conducted on data collected from training sessions. It is likely that disparities between player behaviour in match and training conditions exist, so future work adapting density as a pressure metric should be directed to match play. In AF, it is suggested that match simulations be utilized to achieve this as opposition data is currently restricted during official Australian Football League matches.

Conclusion

This study analysed spatiotemporal data using kernel density estimation to estimate density of players in a continuous manner. This metric was applied in AF training as an alternate measure for the constraint of pressure. Density, relative to the ball-carrier at skill execution, was weakly and positively associated with successful skill performance. These findings contrast with pressure measured through notational analysis. It is suggested that density surrounding the target of a skill execution be considered in future to provide an improved representation of pressure on skill involvements. Increasing the area per player and the number of players in a drill decreases the density on skill involvements. The methods presented here may also be transferred to other sports and be used to contextualize player behaviour in competition and for consideration when designing training environments.

Disclosure of interest

The authors report no conflict of interest.

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ORCID

Ben Teune http://orcid.org/0000-0003-4437-535X
Alice J Sweeting http://orcid.org/0000-0002-9185-6773
Carl Woods http://orcid.org/0000-0002-7129-8938
Sam Robertson http://orcid.org/0000-0002-8330-0011

References

Andrienko, G., Andrienko, N., Budziak, G., Dykes, J., Fuchs, G., Von Landesberger, T., & Weber, H. (2017). Visual analysis of pressure in football. *Data Mining and Knowledge Discovery*, *31*(6), 1793–1839. https://doi.org/10.1007/s10618-017-0513-2

Baumeister, R. F., & Showers, C. J. (1986). A review of paradoxical performance effects: Choking under pressure in sports and mental tests. *European Journal of Social Psychology*, *16*(4), 361–383. https://doi.org/10.1002/ejsp.2420160405

Bonney, N., Ball, K., Berry, J., & Larkin, P. (2020). Effects of manipulating player numbers on technical and physical performances participating in an Australian football small-sided game. *Journal of Sports Sciences*, *38*(21), 2430–2436. https://doi.org/10.1080/02640414.2020.1787697

Browne, P. R., Sweeting, A. J., Davids, K., & Robertson, S. (2019). Prevalence of interactions and influence of performance constraints on kick outcomes across Australian Football tiers: Implications for representative practice designs. *Human Movement Science*, *66*, 621–630. https://doi.org/10.1016/j.humov.2019.06.013

Csataljay, G., James, N., Hughes, M., & Dancs, H. (2013). Effects of defensive pressure on basketball shooting performance. *International Journal of Performance Analysis in Sport*, *13*(3), 594–601. https://doi.org/10.1080/24748668.2013.11868673

Davids, K. (2012). Learning design for nonlinear dynamical movement systems. *The Open Sports Sciences Journal*, *5*(1), 1. https://doi.org/10.2174/1875399X01205010009

Davids, K., Button, C., & Bennett, S. J. (2008). *Dynamics of skill acquisition: A constraints-led approach*. Human Kinetics. http://www.humankinetics.com/products/showproduct.cfm?isbn=9780736036863

Eysenck, M. W. (2013). *Anxiety: The Cognitive Perspective*. Psychology Press.

Fernandez, J., & Bornn, L. (2018). Wide open spaces: A statistical technique for measuring space creation in professional soccer. In *Sloan sports analytics conference, 2018*. Boston, MA.

Glazier, P. S. (2017). Towards a grand unified theory of sports performance. *Human Movement Science*, *56*, 139–156. https://doi.org/10.1016/j.humov.2015.08.001

Ireland, D., Dawson, B., Peeling, P., Lester, L., Heasman, J., & Rogalski, B. (2019). Do we train how we play? Investigating skill patterns in Australian football. *Science and Medicine in Football*, *3*(4), 265–274. https://doi.org/10.1080/24733938.2019.1595111

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33* (1), 159–174. JSTOR. https://doi.org/10.2307/2529310

Link, D., Lang, S., & Seidenschwarz, P. (2016). Real time quantification of dangerousity in football using spatiotemporal tracking data. *PLoS ONE*, *11*(12), 12. https://doi.org/10.1371/journal.pone.0168768

Lucey, P., Bialkowski, A., Monfort, M., Carr, P., & Matthews, I. (2014). "Quality vs quantity": Improved shot prediction in soccer using strategic features from spatiotemporal data. In *Proc. 8th annual mit sloan sports analytics conference*, (pp. 1–9). Boston, MA.

McGarry, T. (2009). Applied and theoretical perspectives of performance analysis in sport: Scientific issues and challenges. *International Journal of Performance Analysis in Sport*, *9*(1), 128–140. https://doi.org/10.1080/24748668.2009.11868469

Newell, K. M. (1986). Constraints on the development of coordination. In M. Wade & H. Whiting (Eds.), *Motor Development in children: Aspects of coordination and control* (pp. 341–360). Martinus Nijhoff.

Pill, S. (2014). Informing Game Sense pedagogy with constraints led theory for coaching in Australian football. *Sports Coaching Review*, *3*(1), 46–62. https://doi.org/10.1080/21640629.2014.890778

Pocock, C., Bezodis, N. E., Davids, K., & North, J. S. (2018). Hot hands, cold feet? Investigating effects of interacting constraints on place kicking performance at the 2015 Rugby Union World Cup. *European Journal of Sport Science*, *18*(10), 1309–1316. https://doi.org/10.1080/17461391.2018.1486459

Robertson, S., Spencer, B., Back, N., & Farrow, D. (2019). A rule induction framework for the determination of representative learning design in skilled performance. *Journal of Sports Sciences*, *37*(11), 1280–1285. https://doi.org/10.1080/02640414.2018.1555905

Silva, P., Esteves, P., Correia, V., Davids, K., Araújo, D., & Garganta, J. (2015). Effects of manipulations of player numbers vs. Field dimensions on inter-individual coordination during small-sided games in youth football. *International Journal of Performance Analysis in Sport*, *15*(2), 641–659. https://doi.org/10.1080/24748668.2015.11868821

Simonoff, J. S. (1996). *Smoothing methods in statistics*. Springer-Verlag. https://doi.org/10.1007/978-1-4612-4026-6

Spencer, B., Bedin, T., Farrow, D., & Jackson, K. (2018). A method for evaluating player decision-making in the Australian football league. In *Proceedings of 14th Australasian conference on mathematics and computers in sport*, (pp. 7–12). Sunshine Coast, Australia.

Spencer, B., Morgan, S., Zeleznikow, J., & Robertson, S. (2017). Measuring player density in Australian rules football using gaussian mixture models. *Complex Systems in Sport, International Congress Linking Theory and Practice 5*, 172–174. https://doi.org/10.3389/978-2-88945-310-8

Timmerman, E. A., Farrow, D., & Savelsbergh, G. J. (2017). The effect of manipulating task constraints on game performance in youth field hockey. *International Journal of Sports Science & Coaching*, *12*(5), 588–594. https://doi.org/10.1177/1747954117727659

Timmerman, E. A., Savelsbergh, G. J. P., & Farrow, D. (2019). Creating appropriate training environments to improve technical, decision-making, and physical skills in field hockey. *Research Quarterly for Exercise and Sport*, *90*(2), 180–189. https://doi.org/10.1080/02701367.2019.1571678

Vilar, L., Araújo, D., Davids, K., Correia, V., & Esteves, P. T. (2013). Spatial-temporal constraints on decision-making during shooting performance in the team sport of futsal. *Journal of Sports Sciences*, *31*(8), 840–846. https://doi.org/10.1080/02640414.2012.753155

Woods, C. T., Jarvis, J., & McKeown, I. (2019). Differences between Elite and Semi-Elite Australian Football Conceptualised through the Lens of Ecological Dynamics. *Sports*, *7*(7), 159. https://doi.org/10.3390/sports7070159

Woods, C. T., McKeown, I., Rothwell, M., Araújo, D., Robertson, S., & Davids, K. (2020). Sport practitioners as sport ecology designers: How ecological dynamics has progressively changed perceptions of skill "acquisition" in the sporting habitat. *Frontiers in Psychology*, *11*, 654. https://doi.org/10.3389/fpsyg.2020.00654