TITLE

Identification of movement categories and associated velocity thresholds for elite Gaelic football and hurling referees

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ABSTRACT

The purpose of this study was to generate movement category velocity thresholds for elite Gaelic football (GF) and hurling referees using a two-stage unsupervised clustering technique. Activity data from 41 GF and 38 hurling referees was collected using global positioning system technology during 338 and 221 competitive games, respectively. The elbow method was used in stage one to identify the number of movement categories in the datasets. In stage two, the respective velocity thresholds for each category were identified using spectral clustering. The efficacy of these thresholds was examined using a regression analysis performed between the median of each of the velocity thresholds and the raw velocity data. Five velocity thresholds were identified for both GF and hurling referees (mean ± standard deviation: GF referees; 0.70±0.09, 1.66±0.19, 3.28±0.41, 4.87±0.61, 6.49±0.50 $m \cdot s^{-1}$; hurling referees; 0.69±0.11, 1.60±0.25, 3.09±0.52, 4.63±0.58, 6.35±0.43 $m \cdot s^{-1}$). With the exception of the lowest velocity threshold, all other thresholds were significantly higher for GF referees. The newly generated velocity thresholds were more strongly associated with the raw velocity data than traditional generic categories. The provision of unique velocity thresholds will allow applied practitioners to better quantify the activity profile of elite GF and hurling referees during training and competition.

KEY WORDS.

GPS, data mining, zones, unsupervised learning, activity profile, team sport.

INTRODUCTION

Advances in player tracking technology has greatly facilitated activity monitoring of athletes participating in invasion field-based team sports. Indeed, activity monitoring is now routine during training and competition (Whitehead et al., 2018). Global positioning systems (GPS) technology in particular, provide large quantities of data on the location at a specific time point from which individual velocities and distances can be quantified. These distances are typically summarised into a number of velocity-based movement categories that vary in intensity and are associated with verbal descriptors, such as low, moderate or high-speed running (HSR) (Whitehead et al., 2018).

Gaelic football (GF) and hurling are intermittent invasion field-based team sports. Games are played between two teams comprising 15 players each, on a playing area of ~130-145 m x 80-90 m (Gamble et al., 2019; Young et al., 2018). Similar to other invasion field-based team sports such as soccer and Australian football, GF and hurling involve brief high-intensity efforts interspersed with low-intensity activity, performed over two 35-minute periods (Collins et al., 2018; Gamble et al., 2019; Malone et al., 2016; Young et al., 2018). GF and hurling are officiated by a referee with assistance from two side-line officials who are responsible for ensuring that games are played in accordance with the rules. To ensure optimal positioning for decision-making, the referee must keep up with play at all times (Weston et al., 2012). This requires the development and maintenance of a high level of physical fitness (Castillo et al., 2016; Weston et al., 2012). Activity data from a large number of studies involving inter-county GF and hurling players has facilitated the design and implementation of game-specific conditioning drills (Malone et al., 2016; Malone et al., 2017). In contrast, no studies have examined the physical demands or physiological responses of GF or hurling referees during competitive games, limiting the development of referee-specific conditioning programmes.

A number of studies have examined the activity profile of referees in soccer and rugby (Brightmore et al., 2016; O'Hara et al., 2013; Weston et al., 2011). These studies have frequently applied velocity thresholds originally used in the analysis of elite male soccer players (Rampinini et al., 2007). Referees are typically older than players, and the failure to account for age-related declines in aerobic capacity and the ability of the muscle to generate force (Castillo et al., 2016; Tieland et al., 2018) may result in an underrepresentation of the physical demands experienced by referees. This highlights the need for cohort-specific movement category velocity thresholds.

Physical performance indicators (e.g. maximum sprint speed) and physiological thresholds (e.g. ventilatory threshold) have been used previously to relativise activity data (Lovell & Abt, 2013; Reardon et al., 2015). However, there is currently no consensus on the most appropriate method or how such thresholds relate to the activity pattern of referees during invasion field-based team sports (Carling, 2013). With sampling rates of micro-technology devices increasing, sophisticated data analytical methods are being used to analyse and relativise activity data (Park et al., 2019; Sweeting et al., 2017). Unsupervised clustering algorithms, a commonly used data mining technique when undertaking multivariate data analysis (Wang et al., 2018), organise data samples into distinct groups known as 'clusters' based on a certain similarity measure (Ofoghi et al., 2013). Spectral clustering is a graph-based approach used to cluster multivariate data by dividing data points into groups such that data points in the same group are heavily connected and data points in different groups are not connected (von Luxburg, 2007). This approach has become a popular method of clustering due to its ability to overcome some limitations of traditional clustering techniques such as *k*-means (von Luxburg, 2007). A spectral clustering algorithm applied to activity data of elite women's soccer players generated four unique velocity thresholds (Park et al., 2019). These thresholds presented logical validity and resulted in practically meaningful differences in the distances covered at high and very high speed compared to thresholds derived from other data mining techniques (Park et al., 2019).

The primary aim of the present study was to generate movement category velocity thresholds for elite GF and hurling referees using a two-stage unsupervised clustering technique applied to activity data. The relation of the categories with the original data was examined and compared to generic velocity thresholds frequently used in the analysis of invasion field-based team sport players and referees. The secondary aim was to quantify the distances covered in the newly generated movement categories and compare these values to the existing generic movement categories. It was hypothesised that the movement category velocity thresholds generated would be lower than those frequently used in the analysis of invasion field-based team sport players and referees.

METHODS

Participants

Forty-one elite inter-county GF (Age: 38.9±4.6 years) and 38 elite inter-county hurling (Age: 40.1±4.5 years) referees (P=0.002) provided written informed consent to participate in the study. Ethical approval was obtained from Dublin City University Research Ethics Committee (DCUREC/2018/041) in accordance with the declaration of Helsinki. The study participants were all members of the Gaelic Athletic Association (GAA) national league and senior championship referee panel which is selected at the beginning of each competitive season. A total of 559 full game datasets were collected between 2016 and 2019 (338 GF, 221 hurling).

Methodology

The national league (NL), scheduled between January and April, and the All-Ireland Championship (AIC) between May and September are the two major competitions contested annually. The dataset in the present study comprises games throughout both competitions including multiple GF and hurling AIC finals. During each game referees wore 10-Hz GPS devices (STATSports, Newry, Ireland), midway between the scapulae in a custom-made undergarment. In order to establish a GPS satellite lock, devices were activated a minimum of 15-min prior to the start of each game (Malone et al., 2017). The validity and reliability of these devices has been previously reported (Beato et al., 2018a; Beato et al., 2018b). Data from the GPS device was downloaded into the STATSports analysis software and separated into first and second halves, excluding the warm-up and halftime period. The raw data was then exported into Python (v.3.7) programming language (Python Software Foundation, Wilmington, DE, USA) for further analysis.

Data points were excluded if instantaneous velocity was >10 m·s^{-1} or instantaneous acceleration was ±6 m·s^{-2} (Park et al., 2019). Data pertaining to the horizontal dilution of precision (HDOP) and the number of satellites locked to the device was available for all datasets collected during 2018 and 2019 (n=423). Data points from these files were excluded from the analysis if the HDOP was >2.0 or if the number of satellites locked to the device was <8 (Malone et al., 2017). Match files in which excluded data accounted for >3% of game time were removed from the analysis (n=5). This resulted in a final dataset of 554 full game datasets (333 GF, 221 hurling), with a median of 6 full game datasets per referee (μ=8.1 games; range: 1-25 games) for GF and a median of 4 full game datasets per referee (μ=5.8; range 1-16) for hurling.

Unsupervised clustering technique

To generate a set of movement category velocity thresholds, the raw data was analysed using an unsupervised clustering technique in two distinct stages, each of which was completed separately for GF and hurling referees. Spectral clustering was used to convert continuous velocity measurements into categorical variables at the points which represent the minimal number of traversals. Data was prepared for spectral clustering using a similar method to that outlined previously in women's soccer whereby the change in velocity from one time point to the next was considered to be a traversal (Park et al., 2019). Traversals between each velocity within the range of velocities 0 m·s^{-1} to 10.0 m·s^{-1}, and of width 0.1 m·s^{-1} were computed and analysed with the spectral clustering algorithm. Spectral clustering treats each velocity as a category, disregarding the rank order (Park et al., 2019). In this regard, 1.0 m·s^{-1} may be grouped with 6.0 m·s^{-1}. To overcome this, a β-coefficient of 0.1 was applied as a smoothing factor to ensure that velocities with no connected edges cannot be clustered together as recommended previously (Park et al., 2019).

The first stage involved determining the number of clusters *k* within the dataset. Firstly, the traversals of each individual game were merged to form one dataset. The spectral clustering algorithm was then repeatedly applied to this dataset for a range of *k* values (1–8). The within-cluster sum of squares for each value of *k* was computed and plotted with the point of inflection considered the most appropriate value. This approach is known as the elbow method and is commonly used in cluster analysis to determine the number of categories (Wang et al., 2018). Having identified the appropriate value of *k*, the second stage involved identifying the values for each of the *k* clusters within the individual games. Spectral clustering was applied to each game separately using the value of *k* discerned in stage one to determine the value of each threshold. Group-based categories were then formed using the mean value of each threshold from the individual games.

Category evaluation

In order to assess if the proposed velocity thresholds for each movement category reflected the original velocity data a regression analysis was performed between the raw velocities at each time point, *i* for each observation *j* (X_{ij}) and the median values within each movement category (M_k). The maximum velocity within each game was identified. These velocities were subsequently separated into three even groups, reflective of the distribution of the maximum velocity. A random sample of three games from each of these groups were taken and analysed with regression analysis using the following formula.

$$X_{ij} = \alpha + \beta M_k + \epsilon_{ij} \qquad \text{(Eq.1)}$$

The coefficient of determination was used to estimate how much variance in the raw data was explained by the newly generated movement category velocity thresholds (Eq.1). The variance explained by the newly generated thresholds was compared to the generic thresholds of 0.2, 2.0, 4.0, 5.5 and 7.0 m·s^{-1} for standing, walking, jogging, running, HSR and sprinting, respectively, which are frequently used in the analysis of invasion field-based team sport players and referees (Brightmore et al., 2016; O'Hara et al., 2013; Rampinini et al., 2007; Weston et al., 2011).

Statistical analysis

Statistical analysis was completed using the Statistical Package for the Social Sciences (v.25) (IBM, Chicago, IL, USA). Data are presented as mean ± standard deviation (SD), unless otherwise stated. The difference between groups for the velocity thresholds and total distance covered in each movement category was assessed using an independent samples t-test. The distance covered in each movement category using the newly identified velocity thresholds was compared to the generic movement categories with velocity thresholds of 0.2, 2.0, 4.0, 5.5 and 7.0 $m \cdot s^{-1}$ using a paired samples t-test. Estimates of effect size were determined using Cohen's *d* with values of 0.2, 0.5 and 0.8 interpreted as small, medium and large effects respectively (Cohen, 1969). For null hypothesis statistical testing, the significance level was set at $\alpha \leq 0.05$ for all tests.

RESULTS

Movement categories

The value for *k* which corresponded to the inflection point was five for both GF and hurling referees. The mean ± SD for each velocity threshold was 0.70±0.09, 1.66±0.19, 3.28±0.41, 4.87±0.61, 6.49±0.50 $m \cdot s^{-1}$ for GF referees and 0.69±0.11, 1.60±0.25, 3.09±0.52, 4.63±0.58, 6.35±0.43 $m \cdot s^{-1}$for hurling referees. The values for all velocity thresholds, except the first threshold were significantly different between GF and hurling referees. Six unique movement categories were then created for GF and hurling referees from the velocity thresholds (Table 1).

[Table 1 near here]

Regression analysis

The results from the regression analysis spanning the three groups generated from the maximal velocity distribution are summarised in Table 2. Across the subset of games, the newly generated velocity thresholds accounted for a larger proportion of the variation in the raw data (Adj.R^2=0.925 and 0.927) compared to the generic velocity thresholds (Adj. R^2=0.894 and 0.895) for GF and hurling referees, respectively.

[Table 2 near here]

Activity profile

The mean ± SD total distance covered by GF and hurling referees during match play was 9418±706 m and 9374±785 m, respectively (P=0.503, *d*=0.06). The distances covered in the very low-speed movement (VLSM) (P<0.001, *d*=0.34), walking (P<0.001, *d*=0.60), low-speed running (LSR) (P<0.001, *d*=1.27), moderate-speed running (MSR) (P<0.001, *d*=0.33), HSR (P<0.001, *d*=0.91) and very high-speed running (VHSR) (P=0.021, *d*=0.19) categories were different between GF and hurling referees (Table 3). The mean ± SD maximum speed achieved was 6.73±0.51 and 6.61±0.43 $m \cdot s^{-1}$ ($P=0.002$, $d=0.25$) for GF and hurling referees, respectively.

A comparison of the total distance covered within each of the newly generated movement categories to the total distance covered using the generic movement category velocity thresholds is shown in Figure 1. The total distance covered using the newly generated movement category velocity thresholds for HSR was higher for GF referees ($P<0.001$, $d=2.90$) and hurling referees ($P<0.001$, $d=2.79$) than the generic HSR category velocity threshold. The total distance covered using the newly generated movement category velocity thresholds for VHSR was higher for GF referees ($P<0.001$, $d=0.61$) and hurling referees ($P<0.001$, $d=0.68$) than the generic sprinting category velocity threshold.

[Table 3 near here]

[Figure 1 near here]

DISCUSSION

The primary aim of this study was to generate movement category velocity thresholds for GF and hurling referees. Using a two-stage unsupervised clustering technique, six unique movement categories and their respective velocity thresholds were determined for GF and hurling referees. These thresholds were subsequently compared to generic velocity thresholds that have been frequently used in previous studies analysing invasion field-based team sport players and referees. The newly generated velocity thresholds had a stronger relation with the raw velocity data and resulted in significantly higher HSR and VHSR distances for GF and hurling referees compared to the generic thresholds. This is the first study to generate unique velocity thresholds for GF and hurling referees and to report data on the activity profile of GF and hurling referees during competitive games.

A number of studies have examined the activity profile of invasion field-based team sport referees (Brightmore et al., 2016; O'Hara et al., 2013; Weston et al., 2011). The movement categories and corresponding velocity thresholds used in these studies were however, developed for players with little consideration given to the potential differences in age or physical capacity of referees (Rampinini et al., 2007; Weston et al., 2011). The use of these velocity thresholds may result in an underestimation of the demands experienced by invasion field-based team sport referees. Unsupervised clustering techniques are becoming increasingly common in the analysis and discretisation of activity data (Park et al., 2019; Sweeting et al., 2017). Application of these techniques present a viable alternative to the use of arbitrary movement classifications and methods reliant upon physical fitness test data (Park et al., 2019).

In the present study, a number of steps were taken to demonstrate the utility of the movement category velocity thresholds generated using unsupervised clustering. The first stage of the unsupervised clustering technique applied the elbow method in an attempt to limit the potential for error or bias in identifying the number of discrete movement categories. Considering that an increase or decrease in the number of movement categories in a dataset alters their dispersion, this method provides a practical assessment of the appropriate number of partitions in the dataset (Wang et al., 2018). The number of movement categories identified for GF and hurling referees is similar to the number often used in the analysis of the activity profile of invasion field-based team sport players (Gamble et al., 2019; Rampinini et al., 2007; Young et al., 2018). The nomenclature used to describe these categories is also similar. As there is currently no consensus regarding the velocity threshold for sprinting among athletes participating in invasion field-based team sports (Sweeting et al., 2017), VHSR was used to denote the highest velocity category for GF and hurling referees. The dataset in the present study is also considerably larger than in previous studies using unsupervised clustering techniques to generate velocity thresholds (Park et al., 2019; Sweeting et al., 2017). Games analysed were collected across four competitive seasons, involve the entire panel of elite GF and hurling referees, every phase of the NL and AIC and all competing teams.

The second stage of the unsupervised clustering technique generated the velocity threshold for each category on a game-to-game basis. This approach permits the formation of both individual and group-based categories, which is recommended (Abt & Lovell, 2009). As there is currently no standardised method to evaluate the suitability of newly generated velocity thresholds, the present study proposed the use of a regression analysis to establish the strength of relation between the newly generated velocity thresholds and the activity data. The regression analysis objectively demonstrated a stronger association between the newly generated velocity thresholds and the raw velocity data compared to the generic velocity thresholds commonly used in the analysis of elite invasion field-based team sport players and referees (Rampinini et al., 2007). The superior relation with the raw velocity data supports the use of these thresholds in the analysis of activity data from GF and hurling referees.

The significant differences in the velocity thresholds for walking, LSR, MSR, HSR and VHSR and in the dispersion of the total distance covered in each category between GF and hurling referees is an important finding. These differences indicate that cohort-specific velocity thresholds are warranted for the analysis of activity data derived from GF and hurling referees and in the design of conditioning programmes. While hurling referees in the present study are older, and achieved a lower maximum speed during competition than GF referees, it is not possible at this time to conclude that these are the sole factors contributing to these differences or that the differences reflect the lower physical capacity amongst hurling referees. In soccer, the activity profile of the referee is influenced by the players which in turn is influenced by the tactical and technical approaches of their respective teams (Rampinini et al., 2007; Weston et al., 2011). The differences in activity profile between GF and hurling players and in the pattern of play within each sport (Collins et al., 2018; Malone et al., 2016) may also have contributed to the differences in the velocity thresholds observed.

The HSR and VHSR velocity thresholds generated in the present study are ~0.6–0.9 $m.s^{-1}$ lower than the HSR (5.5-7.0 $m{\cdot}s^{-1}$) and sprinting (≥7.0 $m{\cdot}s^{-1}$) thresholds, respectively, that have been applied extensively to elite invasion field-based players and referees (Brightmore et al., 2016; Gamble et al., 2019; Rampinini et al., 2007; Weston et al., 2011; Young et al., 2018). The lower HSR and VHSR velocity thresholds for GF and hurling referees may reflect differences in age and physical capacity between elite players and referees (Castillo et al., 2016; Schmitz et al., 2018; Weston et al., 2011). Indeed, GF and hurling referees in the present study are 10–15 years older than elite players. However, the generic velocity thresholds commonly used in the analysis of elite invasion field-based team sport players and referees are merely arbitrary and do not provide information on the physical capacity of the cohorts for which they were first used (Rampinini et al., 2007). Hence, further research examining the physical capacity of the referees against that of players is required to fully elucidate the reason for these differences.

The combined total distance covered by GF and hurling referees in the two highest velocity movement categories commonly used in previous studies analysing the activity profile of referees, HSR and sprinting, was 325.4 m and 248.5 m, respectively. In contrast, the combined total distance covered by GF and hurling referees in the two highest velocity movement categories in the present study, HSR and VHSR, was 980.1 m and 1,403.2 m, respectively. This equates to increases of 654.7 m and 1,154.7 m for GF and hurling referees, respectively. While the use of the generic velocity thresholds does permit comparison between groups, application of these thresholds in practice would result in a significant underestimation of the HSR and sprinting requirements of GF and hurling referees. The lack of exposure to sufficient volumes of high and very high speed running in training can increase the risk of injury (Malone et al., 2017).

It is important to consider the limitations associated with the velocity thresholds generated in the present study. First, the velocity thresholds were derived from the match activity data which is a representation of the referee's movement during the game only. This data is likely influenced by contextual factors such as game importance or the activity profile of the players which were not examined in the present study. The extent to which these factors influence the activity profile of GF or hurling referees during competitive games is currently unknown. Secondly, since the newly generated velocity thresholds were not examined against a measure of physical or physiological capacity conclusions on the differences in physical capacity between GF and hurling referees or between players of their respective sports cannot be made. In this regard, future studies should examine the relation of the methodology in the present study with a range of physical fitness tests and contextual factors.

PRACTICAL APPLICATIONS

The current study provides researchers and practitioners with cohort-specific movement category velocity thresholds for GF and hurling referees. These categories are derived directly from the match activity data and provide an objective alternative to the generic categories often used in the analysis of invasion field-based team sport referees. The use of these categories in the analysis of activity data resulted in practically meaningful differences in the distance covered within each movement category, in particular, the increased HSR and VHSR distances compared to generic categories. This study is also the first to examine the activity profile of GF and hurling referees during competitive games. This information can inform the development of conditioning programmes for GF and hurling referees to mitigate the risk of injury and ensure appropriate physical development such that they possess the requisite fitness levels needed to officiate.

CONCLUSIONS

The present study adds to the growing body of literature using unsupervised clustering techniques in the discretisation of activity data. This study applied a two-stage unsupervised clustering technique to raw velocity data collected from elite GF and hurling referees. Six movement categories with five unique velocity thresholds were generated for each group. Differences were observed between GF and hurling referees for the velocity thresholds and the distribution of the total distance covered. The newly generated velocity thresholds resulted in significantly larger HSR and VHSR distances compared to generic thresholds for both GF and hurling referees. Based on the present findings, it is recommended that analysis of activity data derived from GF and hurling referees use velocity thresholds of 0.70, 1.66, 3.28, 4.87, 6.49 $m \cdot s^{-1}$ and 0.69, 1.60, 3.09, 4.63, 6.35 $m \cdot s^{-1}$, respectively. This methodology can be extended to the analysis of activity data derived from players and referees of other invasion field-based team sports.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

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TABLES

Table 1. Movement categories of Gaelic football and hurling referees.

	GFR	HLR	P value
VLSM ($m \cdot s^{-1}$)	<0.70	<0.69	0.257
Walking ($m \cdot s^{-1}$)	≥0.70 – 1.65	≥0.69 – 1.59	0.002[a]
LSR ($m \cdot s^{-1}$)	≥1.66 – 3.27	≥1.60 – 3.08	<0.001[a]
MSR ($m \cdot s^{-1}$)	≥3.28 – 4.86	≥3.09 – 4.62	<0.001[a]
HSR ($m \cdot s^{-1}$)	≥4.87 – 6.48	≥4.63 – 6.34	<0.001[a]
VHSR ($m \cdot s^{-1}$)	≥6.49	≥6.35	0.001[b]

[a] P<0.001 vs. GF; [b] P<0.01 vs. GF. GF, Gaelic football; VLSM, very low speed movement; LSR, low speed running; MSR, moderate speed running; HSR, high speed running; VHSR, very high speed running.

Table 2. Regression analysis of the newly generated Gaelic football and hurling referee movement category velocity thresholds versus generic velocity thresholds.

	Unsupervised clustering	Generic velocity thresholds
GFR		
Group 1, game 1	0.927	0.893
Group 1, game 2	0.919	0.879
Group 1, game 3	0.933	0.903
Group 2, game 1	0.929	0.894
Group 2, game 2	0.932	0.905
Group 2, game 3	0.920	0.883
Group 3, game 1	0.936	0.917
Group 3, game 2	0.908	0.875
Group 3, game 3	0.922	0.894
HLR		
Group 1, game 1	0.937	0.902
Group 1, game 2	0.922	0.896
Group 1, game 3	0.931	0.889
Group 2, game 1	0.930	0.903
Group 2, game 2	0.933	0.899
Group 2, game 3	0.941	0.915
Group 3, game 1	0.933	0.907
Group 3, game 2	0.909	0.874
Group 3, game 3	0.905	0.871

Data are presented as adjusted R squared. GFR, Gaelic football referee; HLR, hurling referee.

Table 3. Distance covered in each movement category for Gaelic football and hurling referees.

	GFR	HLR
VLSM (m)	164.1 ± 34.8	152.1 ± 36.2[a]
Walking (m)	2026.8 ± 273.8	1866.9 ± 261.8[a]
LSR (m)	2854.0 ± 395.6	2395.9 ± 323.2[a]
MSR (m)	3407.6 ± 542.3	3582.4 ± 531.1[a]
HSR (m)	940.5 ± 375.0	1359.1 ± 531.2[a]
VHSR (m)	25.0 ± 45.5	17.8 ± 28.3[b]

Data are presented as mean ± SD. [a] $P<0.001$ vs. GFR; [b] $P<0.05$ vs. GFR. GFR, Gaelic football referee; HLR, hurling referee; VLSM, very low speed movement; LSR, low speed running; MSR, moderate speed running; HSR, high speed running; VHSR, very high speed running.

FIGURE CAPTIONS

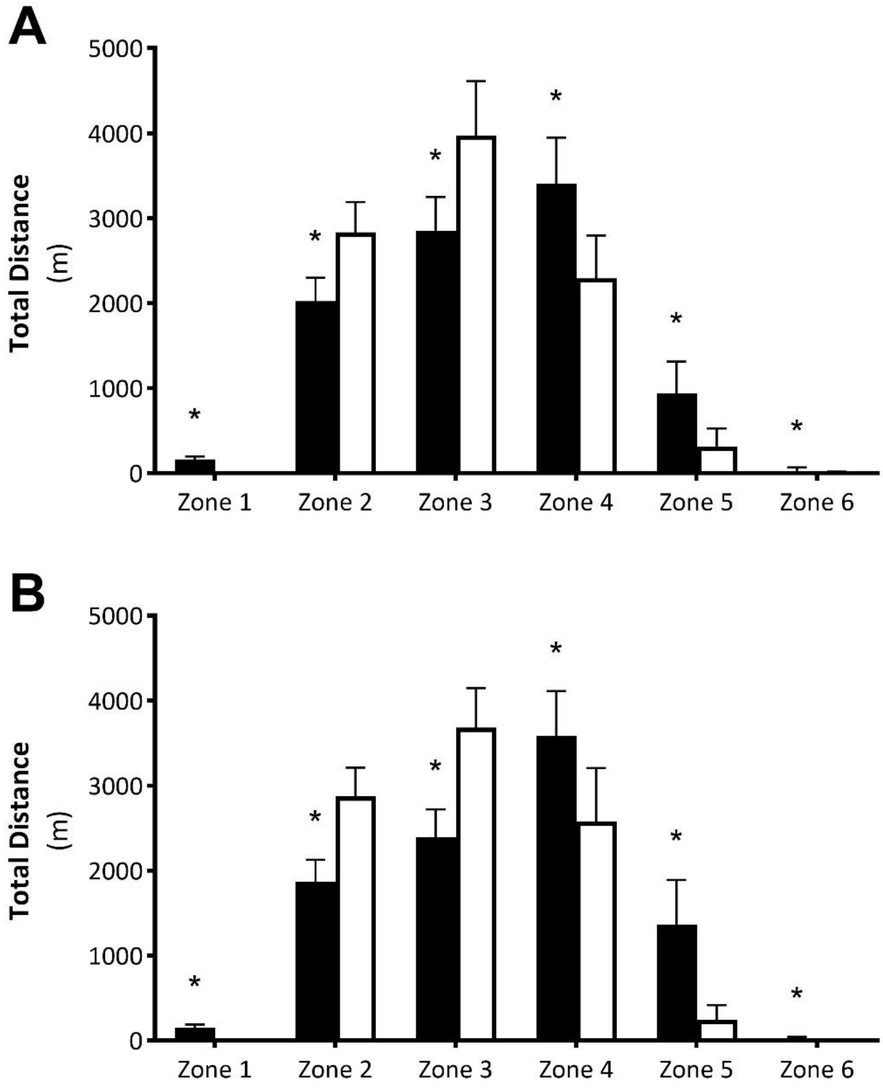

Figure 1. Distance covered within the movement categories generated using the unsupervised clustering technique and the generic movement categories by Gaelic football referees (A) and hurling referees (B). Black bars represent unsupervised clustering technique and white bars represent the generic movement categories. Data are presented as mean with error bars representing SD. *P<0.001 for unsupervised clustering vs generic.