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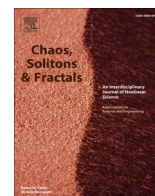
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Elite women's soccer match demand can be described using complexity-based analyses and multifractals

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ABSTRACT

The present study aimed to investigate the variability of the displacements in elite women soccer players during official matches according to the position of the players and to the match progression using non-linear analyses (entropy and multifractal spectrum).

Sixty-three velocity profiles from global positioning devices of elite professional women soccer players were analyzed. The mean, coefficient of variation, and maximum velocity were calculated during the match using four equal segments. Sample entropy and seven parameters derived from the multifractal detrended fluctuation analysis were also calculated. The players were split into five field playing positions: forwards (FW), offensive midfielders (OM), defensive midfielders (DM), central defenders (CD), and lateral defenders (LD).

No significant playing position \times period interaction was found for the different parameters analyzed. However, most parameters showed a significant main effect for playing position ($p < .01$) and period ($p < .01$). Compared to the other players, FW and OM have the lowest entropy. All players showed a dominance of small velocity fluctuations but FW players showed the widest multifractal spectrum primarily. In contrast, CD had a narrow spectrum and reduced amount of small fluctuations. As the game progressed, mean velocity and entropy significantly decreased. In contrast, the multifractal peak value significantly alongside with changes in asymmetry.

From the present results, velocity profiles during elite women's soccer games depicted multifractal features sensitive to player position and match segment, which can help to understand the dynamics and variability of players' responses during a match.

1. Introduction

The demands and characteristics of team sport competitions are frequently explored thanks to the democratization of outdoor and, more recently, indoor tracking systems [1,2]. Soccer has extensively been documented in men, but interests are growing for women studies. For instance, investigations have been developed on injury prevention [3], training and fatigue parameters [4] or menstrual cycle effects [5]. However, physical match characteristics have been less explored [2]. In a recent review [2], the authors noted a wide range in the total distance (between 5.5 and 11.1 km) that increased between playing standards and age groups as a result, for example, of individuals' physical capacities or technical-tactical demands. Moreover, differences between playing positions are often reported. For example, central defenders

have been shown to cover the lowest total distance and distances at specific speeds as compared to midfielders [6].

These last findings underlined the great variability of the behavior of activity profiles during soccer matches. The amplitude of variability could be quantified using various measures such as the coefficient of variation or standard deviation [7]. For instance, authors have shown that the magnitude of variability increased as the match progressed [7]. However, these linear variables, which are commonly used to analyze in soccer, are not the most adequate methods to analyze soccer matches. While these values attest the magnitude of the variability, they do not provide information about the structure of the variability (i.e., the regularity or periodicity of these variations). Non-linear analyses may be alternative signal computing that can witness such various magnitudes and temporal dynamics [8]. As the game progressed, the magnitude of

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variability increased alongside with an increased regularity (i.e., decrease in entropy) [7]. Moreover, as studies have reported that soccer matches have an open, dynamic and complex profile that may be influenced by player interaction and possible random environmental factors [9], complexity-based methods might reveal additional information-rich variability [10]. It has been widely used to study human movement behavior and many biological signals [11,12]. In soccer, complexity-based methods (such as entropy or fractality) can provide insight into individual or collective performance analyses [13]. Entropy, an index of the irregularity of a time series, has previously been used in soccer [14–19]. For example, it has been used to study tactical behavior using team positioning data [14]. Such analysis showed different tactical behaviors considering the variability of the distance of a player dyad (i.e., the association between a player and his teammate/opponent) during different conditions of a given small-sided game [19]. Fractals and multifractals have also been used in soccer [8,20,21] to explore the variability structure of the displacement of the players. For example, the variability of displacements (range of a multifractal spectrum) during small-sided games has been shown to increase with increasing the number of players with a dominance of small fluctuations as compared to large fluctuations [8].

Given that soccer has a complex dynamical behavior, non-linear analyses are of interest to better describe competitions and training. However, complexity-based analyses remain scarce more particularly in elite women soccer. Accordingly, the present study aimed to investigate the variability of the displacements in elite women soccer players during official matches according to the position of the players and to the match progression. Entropy and multifractals parameters were calculated on velocity data extracted for global positioning devices. We hypothesized a greater variability for midfielders as compared to the other playing positions and a greater variability at the beginning of the match. The results of the present study would help the training staff to improve match and training quantification and prescription.

2. Materials & methods

2.1. Participants

Sixteen elite professional women soccer players competing in a French first division team (age: 24.4 ± 3.6 years, height: 168.9 ± 6.1 cm and body mass: 63.1 ± 6.3 kg) were considered. Goalkeepers were not included. Volunteers gave written informed consent for inclusion before participating in the study. The study was approved by the Institutional Review Board. Data were collected during the official 2021/2022 season. A total of 16 different matches was considered. According to global positioning system (GPS) availability, potential data lost, and players involved during the entire match, a total of 63 GPS files was considered for analyses: 11 for forwards (FW), 11 for offensive midfielders (OM), 12 for defensive midfielders (DM), 11 for central defenders (CD) and 19 for lateral defenders (LD).

2.2. Data recording, and processing

Players wore a portable GPS tracking device (Polar Team Pro, Polar Electro, Kempele, Finland) sampling at 10 Hz previously validated [22–24]. GPS signals were automatically combined with 200 Hz inertial measurement units to improve spatial accuracy. The GPS system was placed on the chest skin approximately above the xiphoid process, as recommended by the manufacturer. Recording started immediately after a signal was detected (~15 min before the match) and were stopped at the end of the match. During each match, time stamps were manually set in the Polar team software to indicate the start and end of the match.

Raw data were then exported as CSV files for further processing using RStudio (Ver 2023.03.1, Posit Software, PBC, Boston, USA). The velocity time series were considered without any filtering [25]. From these files,

one of the authors (GR), checked the quality of the GPS signals and the start and end times of the matches and half-times according to the different time stamps and match durations (associated with the extra time). Stoppages of the game (e.g., free/corner/goal kick, referee ball, penalty, injury, substitution) were excluded from analyses. Accordingly, analyses were performed during four segments of equal duration (Q1, Q2, Q3 and Q4 were the first, second, third and last quarters of the match, respectively). Eleven velocity-derived parameters were calculated for these four segments. The mean, coefficient of variation and maximum value of the velocity are regularly used as linear-based parameters [7]. Sample entropy, Hurst exponent, maximum, minimum, peak, width, asymmetry and probability of low fluctuations of the multifractal spectrum were calculated as non-linear values [8,21].

Sample entropy, an index of complexity, was calculated using the “TSEntropies” R package [26]. To be computed, the velocity time series was first embedded in a delayed m -dimensional space. The probability $B^m(r)$ that two sequences match for m points was computed by counting the average number of vector pairs within a tolerance of r . The embedding dimension m was set to length 2 and tolerance r to 0.2 multiplied by the SD of the original time series [17]. This process was repeated for an embedding dimension of $m + 1$ to obtain the probability $A^m(r)$. SampEn was the negative logarithm of the ratio between these two probabilities:

$$\text{SampEn}(m, r) = -\ln(A^m(r)/B^m(r)) \quad (1)$$

The multifractal spectrum was calculated using a multifractal detrended fluctuation analysis (MFDFA) using the “MFDFA” R package [27]. The detrended profile was obtained while calculating the cumulative sum of the velocity time series x_i (with N data points) subtracted by the mean. The profile was sub-divided into $N_s = \text{int}(N/s)$ non-overlapping windows of equal length s . The same sub-division was repeated starting from the opposite end to obtain $2N_s$ segments of the time series. A polynomial of order m was fitted to each of the $2N_s$ segments, and the variance was calculated:

$$F(v, s) = \frac{1}{s} \sum_{i=1}^s [Y_{(v-1)s+i} - Y_{(v-1)s+i}]^2 \quad (2)$$

For $v = 1, 2, \dots, N_s$, where $y_{(v-1)s+i}$ is the polynomial function for the segment $Y_{(v-1)s+i}$ of length s . Then, the q th order fluctuation function was computed by averaging over all segments.

$$F_q(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2(v, s)]^{q/2} \right\}^{1/q} \quad (3)$$

The fluctuation function depends on the segment size s and the q th power. $F_q(s)$ increases with increasing s , and demonstrates a linear behavior in the log-log scale for a specific q if it follows a power-law with exponent $h(q)$. $h(q)$ is the generalized Hurst exponent or self-similarity exponent. It is dependent on q when the time series is multifractal. The singularity multifractal spectrum $f(\alpha)$ can subsequently be constructed when considering the fractal exponent function $\tau(q)$:

$$\tau(q) = qh(q) - 1 \quad (4)$$

$$f(\alpha) = q\alpha - \tau(q) \text{ with } \alpha(q) = \frac{d\tau(q)}{dq} \quad (5)$$

In the present study, various m -order polynomial fittings were applied (from $m = 1$ to $m = 5$) with F decreasing with increasing the m -order due to a smaller residual [28]. Because similar F were obtained with $m \geq 3$, we chose the third-order (i.e., $m = 3$) detrended polynomial to perform the MFDFA (Fig. 1B). Similarly, the fluctuation function was constructed with different timescale s and q values. We chose a scaling region with s values starting from 80 samples and ending to 1300 samples for the analysis of match segments. As recommended, minimum scaling values were set to avoid fluctuations close to zero [29]. In

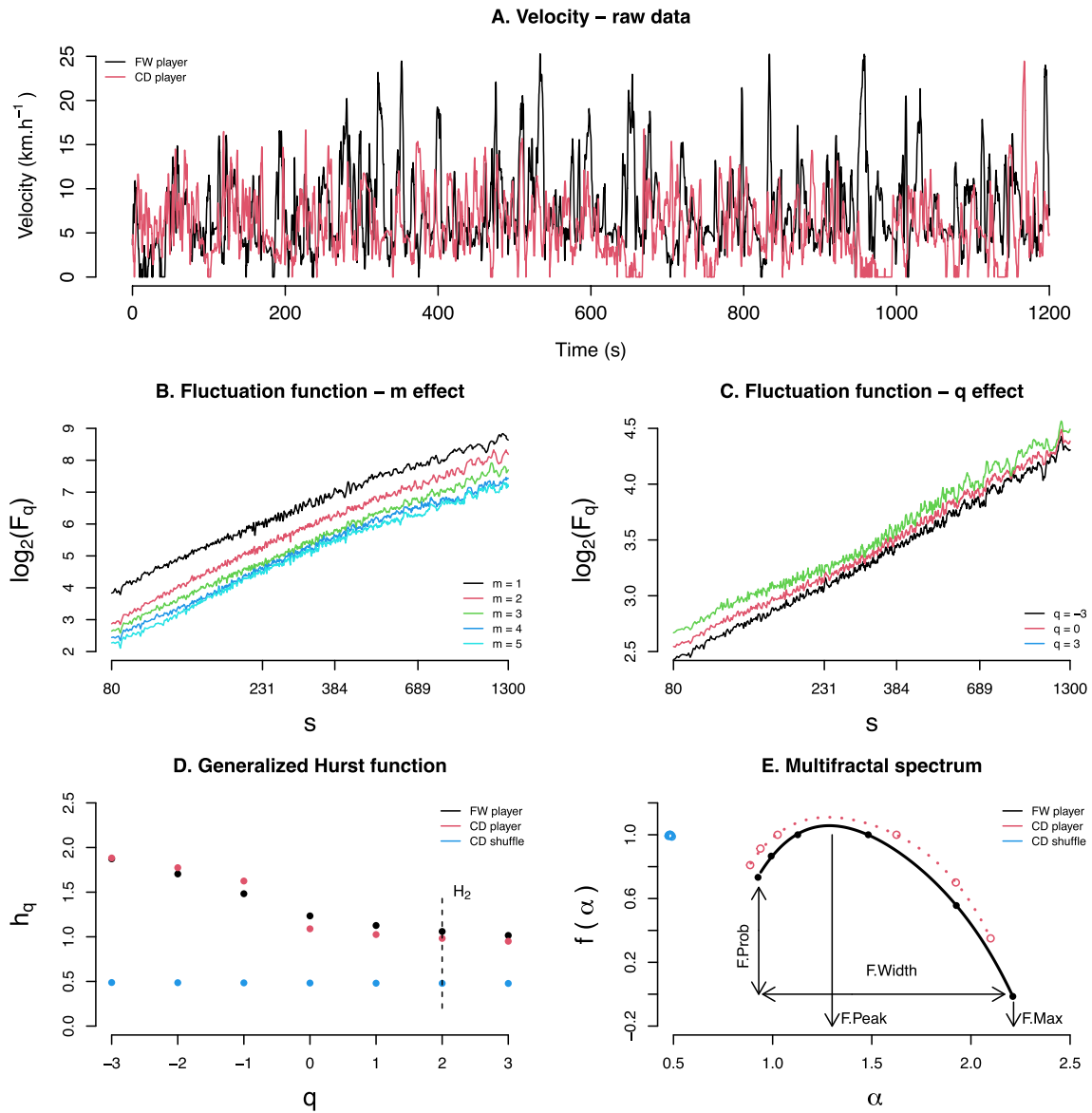


Fig. 1. Illustration of the multifractal detrended fluctuation analysis (MFDFA). A, example of raw velocity data for a forward (FW) and central defender player (CD). B, fluctuation function with different m values (from $m = 1$ to $m = 5$). C, fluctuation function with different q values with $m = 3$. D, Generalized Hurst function for the same player than in A. The dashed vertical line corresponded to the Hurst exponent with $q = 2$ (H_2 : monofractal series). E, Multifractal spectrum. **F.Max** is the maximum α exponent. **F.Peak** is the singularity exponent at peak spectrum. **F.Width** is the total width of the spectrum. **F.Prob** is the probability to have large or small fluctuations. In this example, **F.Prob** revealed a high probability to have large fluctuations. In contrast, the long right tails in this example depicted an asymmetry corresponding to a dominance of local fluctuations with small magnitudes as compared to large fluctuations. Note that for shuffle data produce Hurst exponents close to 0.5 (D) with a very narrow spectrum (E) which illustrated purely random monofractal series.

addition, the maximum values were based on the theoretical length of N to obtain at least 10 segments [29]. Fluctuation functions with linear behavior were only retained for analyses. The linear behavior was attested by coefficients of variation. $R^2 > 0.94$ was used as a cut-off. The generalized Hurst exponent function to q and multifractal spectrum were constructed with $-3 < q < 3$. The decreasing generalized Hurst exponent function witnessed a multifractal feature. The Hurst exponent with $q = 2$ was recorded (H_2). The multifractal characteristics were calculated using six parameters of $f(\alpha)$: i) the width of the multifractal spectrum, ii) the maximum α exponent which corresponded to small fluctuations, iii) the minimum α exponent which corresponded to large fluctuations, iv) the peak exponent which was the singularity exponent at peak spectrum (when $f(\alpha) = 1$), v) the asymmetry calculated as a ratio [12] which represented small fluctuations if < 1 (i.e., right asymmetry witnessed by a long right tail, see Fig. 1E) and vi) the probability to have

large or small fluctuations. The probability to have large or small fluctuations was calculated as the difference in fractal dimension of the maximum and minimum probability subset [8]. In our study, a probability < 0 (shown in Fig. 1E) revealed large fluctuations with more probability throughout the signal as compared to small fluctuations. Finally, in order to verify that our results were not due to chance, we shuffled our real GPS time series. This shuffling procedure was repeated for all GPS time series. The same multifractal procedures were applied to these newly generated shuffled time series. Contrasting from real velocity time series, shuffled data showed reduced dispersion of H_2 with values close to 0.5 (Hurst exponent of purely random series). An illustration of MFDFA for two individuals and for shuffle data is shown in Fig. 1.

2.3. Statistical analyses

Statistical analyses were performed using JASP (version 0.14, JASP Team 2020, University of Amsterdam, available free at <https://jasp-stat.org/download/>). Normality, homoscedasticity and sphericity of the data were tested and confirmed by the Shapiro-Wilk, Levene and Mauchly's tests, respectively. A two-way ANOVA was performed to test playing position × period interactions. Playing positions were FM, OM, DM, CD and LD. Period corresponded to the different quarters of the match (Q1 vs. Q2 vs. Q3 vs. Q4). In case of non-sphericity, a Greenhouse-Geisser correction was applied. Post-hoc tests with Bonferroni corrections were conducted if significant main effects or interactions were present. Partial eta square (η^2) was calculated from ANOVA results, with values of 0.01, 0.06, and above 0.14 representing small, medium and large differences, respectively [30]. $p < .05$ was used as the level of statistical significance for all comparisons. Values are expressed as mean ± SD.

3. Results

No significant playing position × period interaction was observed (Table 1). Significant playing position effects were obtained for most variables (except for the MFDFA asymmetry and probability for small fluctuations). Significant period effects were obtained for the mean velocity, coefficient of variation, sample entropy, the peak, width, asymmetry and probability for small fluctuations of the multifractal spectrum.

3.1. Playing position

The mean velocity was the greatest for DM and the lowest for CD and LD (Fig. 2). The coefficient of variation of the velocity was the lowest for DM and greatest for FW. The maximum velocity was the greatest for FW and LD and the lowest for DM. The sample entropy showed the lowest values for FW and OM as compared to the other positions (Fig. 3). The Hurst exponent (H_2) was the greatest for DM and lowest for CD and LD (Fig. 3). The MFDFA spectrum maximum was greater for FW as compared to CD and LD. The MFDFA spectrum minimum was greater for DM as compared to all other playing positions. The MFDFA spectrum peak and width showed the lowest values for CD and greatest values for FW playing positions.

3.2. Match segments

The mean velocity decreased significantly and progressively during the match (Q1 > Q2 = Q3 > Q4) (Fig. 2). The coefficient of variation of the velocity significantly increased during the match with lower values

during Q1 and greater values during Q4. The sample entropy was significantly greater in Q1 as compared to the other quarters (Fig. 4). The MFDFA spectrum peak increased significantly and progressively during the match (Q1 < Q2 = Q3 < Q4). The MFDFA asymmetry showed the lowest values during Q3. Finally, the MFDFA probability for small fluctuations was significantly greater in Q1 as compared to Q3.

4. Discussion

The present study aimed to investigate the variability of the displacements using entropy and multifractal analyses in women's elite soccer players during official matches according to the position of the players and match progression. Our results confirmed the complex dynamical behavior of elite women soccer players during official soccer games that can be studied using non-linear analyses. Entropy and multifractal parameters revealed playing position and match progression effects.

Playing position was first studied using the mean velocity and maximal velocity. Values are within similar ranges than previously published papers [31,32]. These velocity-based outcomes often showed specific playing position's characteristics [6,33]. Midfielders generally covered the greater distance and had the lowest maximum velocity [6]. Our results confirmed this observation since midfielders had higher mean velocity values (an indirect measure of the total distance) and the lowest maximum speed (more particularly for DM). The lowest mean velocity was obtained for CD and the highest speed for FW and LD. In addition, these parameters showed a progressive displacement decline during the match as shown by the reduction in mean velocity. Again, this result confirmed previous studies since a total distance decreased as the match progressed has been observed concomitant with longer intervals between sprints [34–36]. Although often used as an argument, the variability of the displacement is poorly investigated [2]. In the present study, and as commonly used [7,14,37], we initiated the investigation of the amplitude of variability using coefficients of variation. Our results confirmed previous studies, for example with an increased coefficient of variation during the match progression [7]. This index provides useful information to witness a greater variability in forward players as compared to midfielders and to point out an increased amplitude of variability during the match progression. Interestingly, variability increased during the second half of each half-time without any differences between the beginning of each half-time but a large increase at the end of the match as compared to all other time points. These findings might attest the progression of fatigue during the match. However, linear-based analyses (e.g., coefficient of variation, or standard deviation) have several limitations. The linear measures of variability only provide information on the amplitude of variation and do not explore in depth the structure of the spatio-temporal characteristics of a given time

Table 1
Results of the ANOVA.

Variable	Position effect			Time effect			Position x Time		
	F	p	η^2	F	p	η^2	F	p	η^2
Mean	8.5	<0.001	0.384	44.6	<0.001	0.448	0.5	0.863	0.038
CV	7.8	<0.001	0.362	12.1	<0.001	0.181	1.2	0.273	0.083
Max	12.9	<0.001	0.485	2.6	0.055	0.045	1.3	0.209	0.088
SampEn	12.5	<0.001	0.476	16.0	<0.001	0.226	0.9	0.492	0.065
H_2	9.7	<0.001	0.414	2.7	0.057	0.047	1.0	0.391	0.072
F.MAX	3.7	0.009	0.215	3.3	0.066	0.058	1.4	0.234	0.094
F.MIN	11.1	<0.001	0.449	0.9	0.405	0.017	1.4	0.171	0.094
F.PEAK	11.3	<0.001	0.452	8.7	<0.001	0.138	1.2	0.267	0.085
F.WIDTH	12.0	<0.001	0.467	13.9	<0.001	0.203	1.2	0.261	0.083
F.ASYM	1.7	0.151	0.113	5.4	0.004	0.090	1.4	0.167	0.097
F.PROB	1.0	0.401	0.070	6.4	<0.001	0.104	1.0	0.396	0.072

Mean: mean velocity; CV: coefficient of variation; Max: max velocity; SampEn: sample entropy; H_2 : Hurst exponent with $q = 2$; F.WIDTH: the width of the multifractal spectrum; F.MAX: the maximum α exponent; F.MIN: the minimum α exponent; F.PEAK: singularity exponent at peak spectrum; F.ASYM: asymmetry of the multifractal spectrum; F.PROB: probability for small fluctuations.

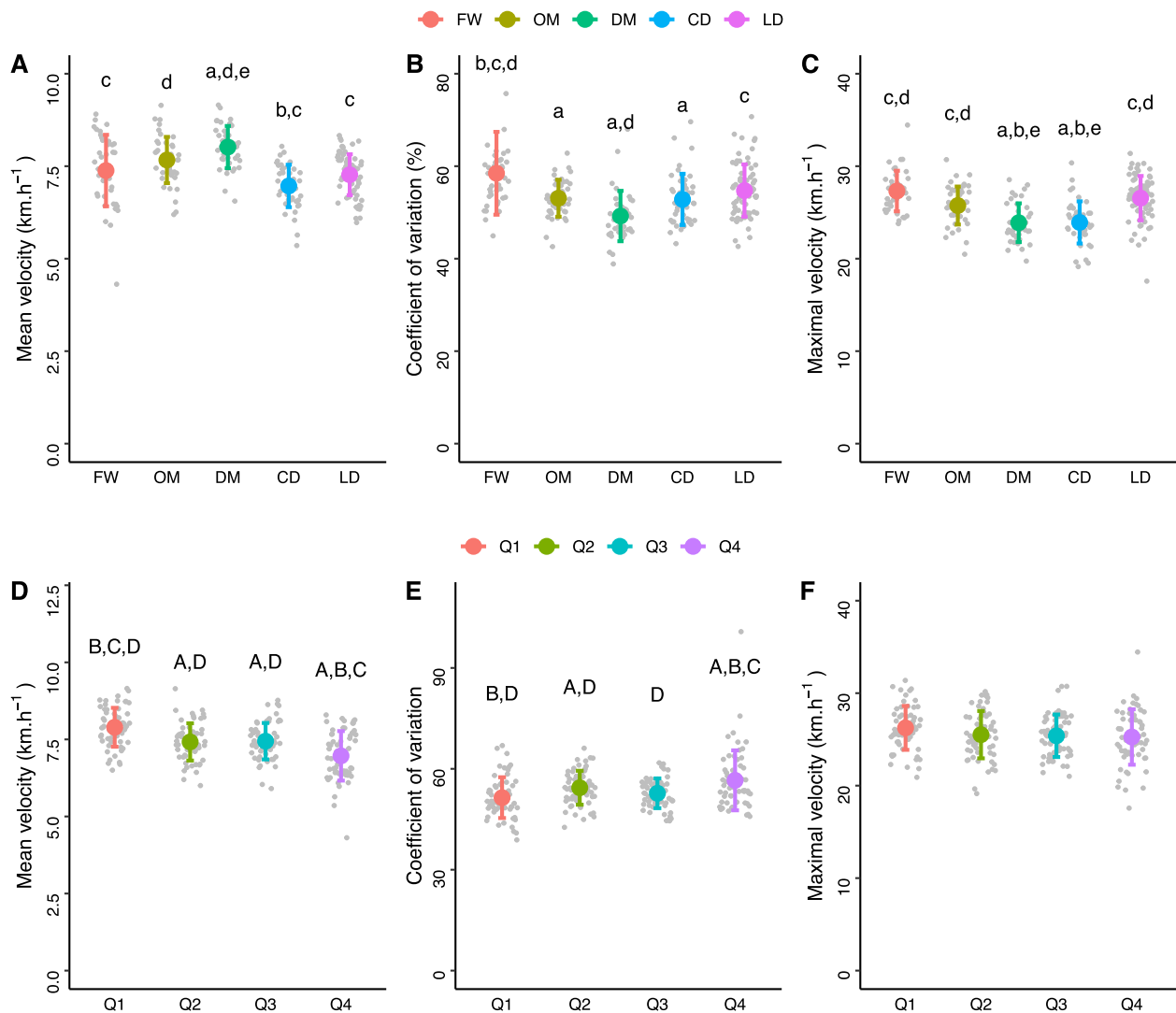


Fig. 2. Linear-based analyses of the velocity during soccer games (mean \pm SD with individual values). The velocity is explored using the mean, coefficient of variation and maximal values as a function of playing positions (panels A, B and C, respectively) and match segments (panels D, E and F, respectively). Significant differences ($p < .05$) with playing positions are shown using letters: a = forwards (FW), b = offensive midfielders (OM), c = defensive midfielders (DM), d = central defenders (CD) and e = lateral defenders (LD). Significant differences ($p < .05$) with the four quarters of the match are shown with capital letters (A = Q1, B = Q2, C = Q3 and D = Q4).

series [7,38,39]. Indeed, linear measures assumes that the variability within a time series is random and independent [40]. However, in numerous biological systems or human movements, variability has deterministic origins with a correlated spatio-temporal structures. For these reasons, non-linear tools, used to study the deterministic chaos, have been applied here to explore how a motor behavior emerges as a function of playing position and time. Entropy, correlation dimension, largest Lyapunov exponent and detrended fluctuation analysis are often used [41]. In the present study, we decided to calculate entropy as an index of complexity/irregularity [42]. In addition multifractals analyses, developed for nonstationary data, were used in order to quantify the presence of long-range correlations alongside with complementary information related to the small and large fluctuations of the velocity [43–45].

Entropy, an index of complexity/irregularity of a time series, was calculated to discriminate the dynamics of the displacement of the players. Low values were computed here, that reveal regular behaviors (i.e., few unpredictability of the displacements fluctuations). Indeed, entropy ranged between 0 and 1 with low values corresponding to high predictability and regularity. In soccer, similar low entropy values have

previously been quantified [15,17,19]. These studies generally considered a player dyad (i.e., player displacement according to his opponent) but no studies have considered playing positioning differences in elite women. Our results revealed greater regularity in offensive players as compared to defensive players.

Interestingly, the greater regularity in offensive players is concomitant with a great quantity of variability as indicated by coefficients of variation. This already observed behavior [7] highlighted different complementary information being obtained from linear and non-linear analyses. Indeed, the coefficient of variation gives evidence of a quantity of variability while entropy characterizes the structure of this variation. The range of variations of the displacements can be further characterized using a MFDFA spectrum. However, very few studies have applied this type of analysis in soccer [8,20,21]. It gives information-rich outcomes to determine whether players use small or large amplitude variations of their displacements. For instance, authors have previously shown smaller displacements fluctuations during small-sided games as compared to jogging or high-intensity training [8]. The level of opposition (i.e., number of players) also influence this dominance of small fluctuations [8].

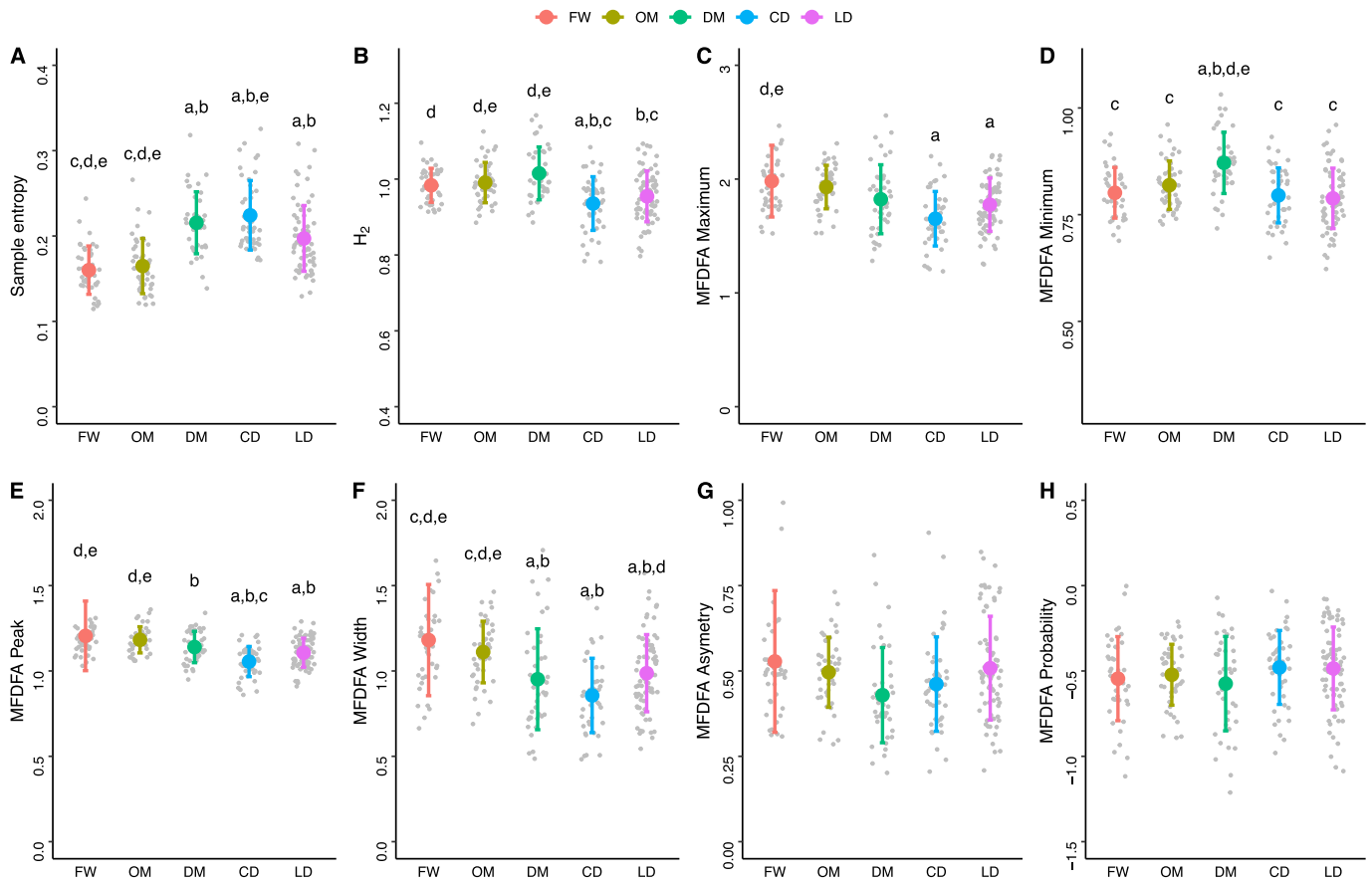


Fig. 3. Non-linear analyses of the velocity during soccer games (mean \pm SD with individual values). Panel A corresponded to the sample entropy. Multifractal detrended fluctuation analysis (MFDFA) is evidenced according to the Hurst exponent (H_2), the multifractal maximum, minimum, peak, width, asymmetry and probability for small fluctuations (panels B, C, D, E, F, G, and H, respectively). Significant differences ($p < .05$) with playing positions are shown using letters: a = forwards (FW), b = offensive midfielders (OM), c = defensive midfielders (DM), d = central defenders (CD) and e = lateral defenders (LD).

The results of our study confirmed a multifractal pattern of the velocity time series. Such affirmation is related to the comparison between actual and shuffled data. Indeed, shuffle time series produced H_2 values ~ 0.5 (witness of purely random values with no memory; Fig. 1D) with a flat generalized Hurst exponent function and very narrow multifractal spectrum (witness of a monofractal pattern; Fig. 1E). In contrast, real velocity time series revealed H_2 values close to 1 that corresponded to an optimized long-range autocorrelated time series and a decreasing generalized Hurst exponent function with q [45]. The different parameters of the MFDFA spectrum, in particular the maximum and width, showed a high degree of multifractality, which is generally observed during tasks of high complexity [8]. Furthermore, the right-skewed asymmetry (< 1) suggested a long-range autocorrelation in small fluctuations for all playing positions. The dominance of small fluctuations has already been observed in soccer [8], which could be attributed to low-intensity actions such as predominantly static, walking or low-intensity running. For instance, the same authors previously observed increased multifractality with very small fluctuations during a circuit activity (with a wide range of speeds and displacement) as compared to constant running activities. Moreover, the MFDFA probability showed negative values corresponding to a high probability of large fluctuations for all playing positions. During matches, it corresponded to a higher probability for high-intensity activities such as high-intensity running or sprinting [8]. These wide, right-skewed spectrums with a higher probability for large fluctuations over small fluctuations have previously been observed in small-sided games, while constant velocities produce the opposite [8].

The MFDFA spectrum revealed a large inter-player dispersion, which

can be attributed to multiple origins such as inter-individual technical skills differences or match contextual variables such as opponents or goals, but also to the computation applied. Despite the large dispersion, some differences were found between playing positions. From the MFDFA spectrum, we obtained a higher multifractality for offensive players (FW and OM) as compared to the other playing positions. The wider spectrum was mostly attributed to small fluctuations and to a rightward shift of the spectrum. To illustrate these findings in practice, although all players continuously adapt their behavior to the opponents or teammates, offensive players have a wider range of activities during the game ranging from long static/walking activities (small velocity fluctuations) and fast displacements in attacking situations (large fluctuations). However, offensive players presented more static/walking activities as compared to the other playing positions which could be attributed to the playing role during the games but also to situational and contextual variables. In contrast, DM presented fewer large fluctuations as compared to all other positions of play. It suggested DM players are less inclined to fast velocity changes than the other players. In addition, our results suggested the multifractal spectrum is sensitive to both large and small fluctuation changes. This conclusion is in contradiction with a previous study which suggested it was not sensitive to capture changes in large fluctuations [8]. These differences could be attributed to the computational methods and to the greater complexity observed during matches as compared to small-sided games. The associated greater minimum α exponent in our present study compared to small-sided games allows for the detection of both large and small fluctuations.

In addition to playing position, entropy and MFDFA spectrum are

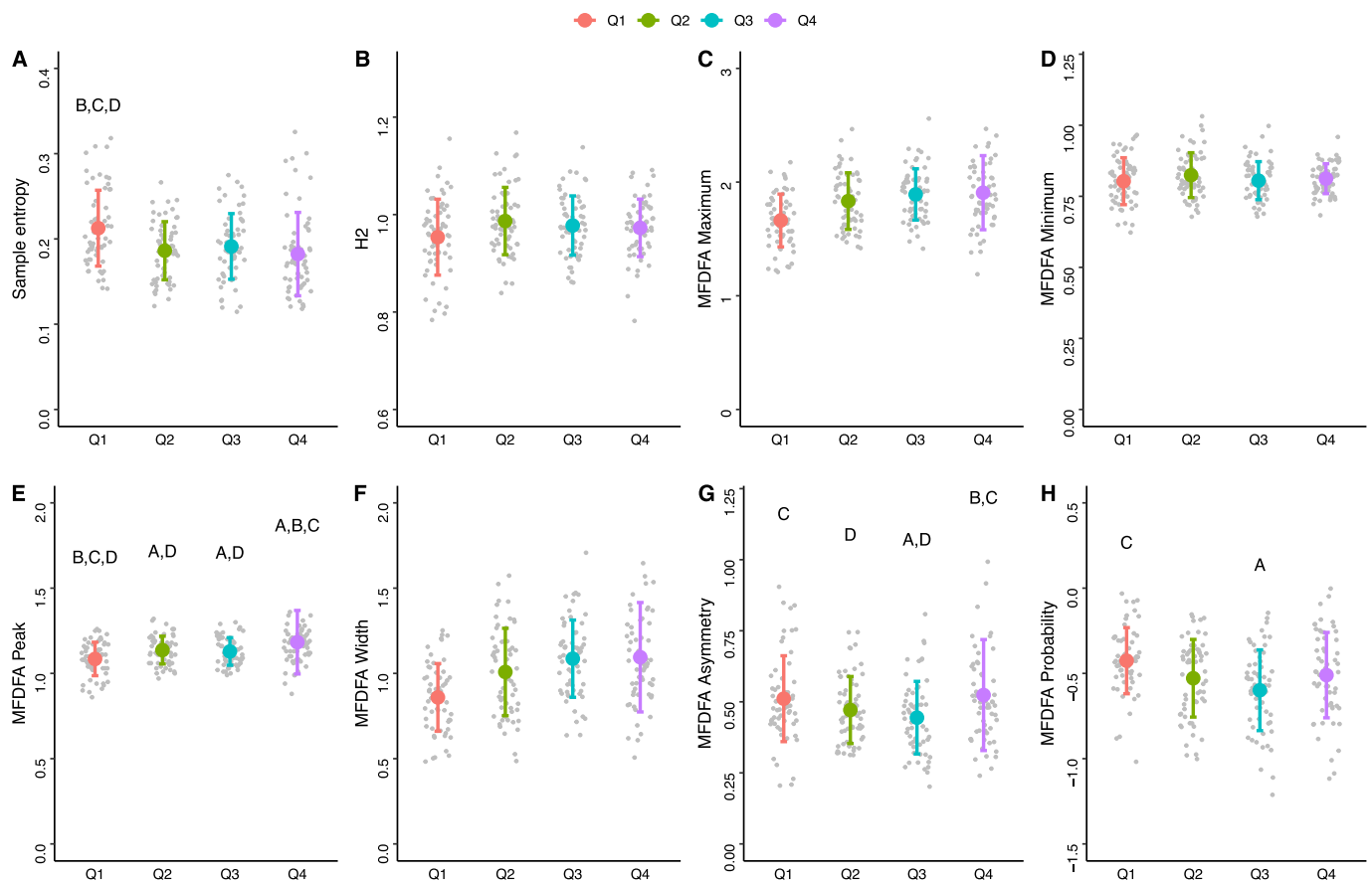


Fig. 4. Non-linear analyses of the velocity during soccer games (mean \pm SD with individual values). Panel A corresponded to the sample entropy. Multifractal detrended fluctuation analysis (MFDFA) is evidenced according to the Hurst exponent (H_2), the multifractal maximum, minimum, peak, width, asymmetry and probability for small fluctuations (panels B, C, D, E, F, G, and H, respectively). Significant differences ($p < .05$) with the four quarters of the match are shown with capital letters (A = Q1, B = Q2, C = Q3 and D = Q4).

influenced by the progression of the match. A greater entropy, witnessing less regularity was obtained at the very beginning of the match as compared to the other match segments. Such an increase in regularity during the game has already been observed [7,15] and has been explained as a team adaptation to a preferred attractor state [7,15]. The stabilization of the displacement obtained in our study could similarly be explained by an increase in fatigue with the progression of the match that would constrain the player to play conservatively, with a reduced degree of freedom (i.e., less and optimized displacements).

Again, the increased regularity is concomitant with an increased quantity of variability as indicated by coefficients of variation. Accordingly, with fatigue, players have more variations of the displacements with more regularity and predictability. Training and expertise will help the player to master this conservative/pacing behavior. Exploring players velocity time series during the match progression gives useful information for the practitioner. Taken together, values revealed a general rightward shift of the MFDFA spectrum with fatigue. Indeed, a significant increase in peak values was obtained alongside with a slight (but non-significant) increase in maximum and width of the multifractal spectrum with the match progression (especially compared to the first quarter). This trend for greater multifractality throughout the game may be indicative of fatigue (alongside with decreases in physical components with the progression of the game [36]). Interestingly, using other biological times series (e.g., electromyography), authors have observed a greater degree of multifractality in fatigued as compared to fresh condition [46,47]. As previously mentioned, the value of asymmetry indicated a dominance of small fluctuations as compared to fast ones. It can confirm the presence of a

smooth and more periodic time series, often considered as suboptimal system, as previously observed by the increased maximum and peak of the MFDFA spectrum with fatigue [48]. However, the higher probability of large fluctuations during the match progression, also confirmed more complex dynamics of displacements alongside with a conservative playing style [7,8,15]. In practice, it suggested a conservative playing style with numerous small fluctuations interspersed with an increased probability for fast displacements with the game progression. This behavior can originate from fatigue, but also to a pattern of displacement adapted to the opponent or to other contextual variables such as goal scoring or tactics.

Our findings confirmed previous results highlighting the need to conduct non-linear analyses for an improved sensitivity to discriminate the dynamics of the displacement of soccer players [7,19,38]. However, all analyses, whether they are linear and non-linear, give a specific key for understanding soccer match demands. Linear-based analyses revealed a decreased displacement with a greater variability during a match. In contrast, non-linear parameters permitted to explain the structure of this greater variability (i.e., more regular with more and dominant small velocity fluctuations). To obtain these results, we decided to consider the time series of each player separately. This one-by-one analysis has the advantage to determine individual responses to a given training intervention or to a match [49]. Given the results of the present study, single analysis only partly describes the physical, technical and/or tactical behavior of each player according to particular contextual variables. Complexity-based analyses in soccer training or match usually applied other non-linear mathematical models such as cross-correlations inside a player dyad or team dynamics [17,19–21]. It

would help understanding the behavior of a player depending on opponents or teammates, i.e., tactics. In a time of big data science, various and multiple analyses [21] should therefore be explored standards in different playing standards, age-group and sex for a better characterization of soccer match demands or for talent detection. Such holistic characterization might also help understanding the modified displacement pattern with the match progression. Indeed, although fatigue was not directly quantified in the present, all non-linear parameters suggest a loss of complexity in the velocity time-series obtained from the GPS data. Physical or mental fatigue, causing a reduced physical performance during and after a soccer match, are frequently investigated [34,35,50]. However, pacing strategies or situational/contextual variables [51] could contribute to the modified activity during a match. The increase in regularity at the end of the game (hypothesized as a conservative style of play) would partly confirm an adapted pacing throughout the match.

5. Conclusion

The findings of the present study confirmed that the complex dynamical behavior of elite women soccer players during official soccer games can be studied using non-linear analyses as complementary methods to the most commonly used linear-based analyses. Entropy and multifractal parameters are sensitive to playing position and match progression effects. Offensive players demonstrated greater velocity regularity than defensive players during the game. The structure of velocity variability was mostly related to small velocity fluctuations. Moreover, and for all playing positions, an increased regularity and predictability was recorded with the progression of the game that can be attributed to fatigue or a conservative behavior at the end of the game as compared to the beginning. We conclude that linear and non-linear analyses provide specific and complementary keys to understanding the demands of soccer matches.

Abbreviations

ANOVA	analysis of variances
F.ASYM	asymmetry of the multifractal spectrum
CD	central defenders
DM	defensive midfielders
FW	forwards
H ₂	Hurst exponent with $q = 2$
LD	lateral defenders
GPS	Global positioning system
F.MAX	maximum α exponent
MFDDFA	multifractal detrended fluctuation analysis
OM	offensive midfielders
F.PEAK	singularity exponent at peak spectrum
η^2	partial eta square
Q1, Q2, Q3 and Q4	first, second, third and last quarters of the match
SD	standard deviation

Ethics approval and consent to participate

Experimental procedures were applied in alignment with the Declaration of Helsinki and its later amendments, and the study was approved by the Ethics Committee for sport science research (IRB00012476-2021-22-04-105). All volunteers signed a written consent for their participation.

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CRediT authorship contribution statement

Nicolas Babault: Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gaelyann Rodot:** Writing – review & editing, Investigation, Formal analysis, Data curation. **Carole Cometti:** Writing – review & editing, Visualization, Conceptualization. **Denis César Leite Vieira:** Writing – review & editing, Validation, Conceptualization.

Declaration of competing interest

The authors declare no competing interests.

Data availability

Data will be made available on request.

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