Journal of Coaching and Sports Science
Volume 2, Issue 2, 65-74.
e_ISSN: 2963-1483
https://www.journal.foundae.com/index.php/jcss/index

Assessing the Amount of Data per Second to Measure Tactical Variables in Team Sports

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Article Info

Article history:
Received: July 25, 2023
Revised: Agustus 18, 2023
Accepted: September 26, 2023

Keywords:
Data filtering;
Data processing;
Game analysis;
Sampling rates;
Technology.

Abstract

The sampling frequency of microsensors that measure the position of the players in team sports is a variable that could affect the accuracy of the measurement. The present study aimed to assess the impact of the sampling frequency on the measurement of a collective tactical behavior variable: the total area (TA). Sixteen young U16 male soccer players participated in the study. They carried out three controlled tasks. The tactical variable was measured by a radio ultra-wideband technology (IMU; WIMU PROTM, RealTrack Systems, Almeria, Spain). For TA, different sampling frequencies were applied (i.e. 1 Hz, 2 Hz, 4 Hz, and 10 Hz). Trivial differences ($p > 0.05$) were found between the TA values across the different amounts of inserted data per second across Task 1 (ES= 0.04-0.08), Task 2 (ES= 0.01-0.09), and Task 3 (ES= -0.03-0.04). Also, *High* to *perfect* ICCs (0.91-1) and linear correlations ($r = 0.961$-1; $p < 0.01$) were found among the TA values obtained through all sampling frequencies. The sampling frequency (i.e., 1 Hz, 2 Hz, 4 Hz, and 10 Hz) does not affect the measurement of the total area during tactical behavior analysis. Still, it does significantly affect the change in centroid position measurement. Thus, using 1 Hz to measure TA is recommended, but further studies should analyze the impact of sampling frequencies lower than 1 Hz and greater than 10 Hz to measure this collective tactical behavior.

To cite this article: Rico-González, M., Arcos, A. L., Rojas-Valverde, D., Gómez-Carmona, C. D., & Pino-Ortega, J. (2023). Assessing the amount of data per second to measure tactical variables in team sports. *Journal of Coaching and Sports Science, 2*(2), 65-74. https://doi.org/10.58524/jcss.v2i2.240

INTRODUCTION

Positioning tracking systems technologies were originally intended for military and scientific use, but in recent years, they have been used for various applications (Malone et al., 2017). For example, the sports area has been a new development niche for outdoor and indoor tracking systems (Frencken, W & Lemmink, K, 2009; Malone et al., 2017; Passos et al., 2008). These new applications have motivated improvements in these types of instruments' positional, computational, and image analyses. Application of position tracking systems in sports was driven by studies led by Schmidt, O'Brien, and Sysko (1999), who opened up new lines of research regarding intra-person and inter-person coordination, making it possible to assess tactical behavior in sports (Schmidt, O' Brien, & Sysko, 1999). Although the authors proposed these methods as tactical measures, they were later called micro-level measures because they only quantified two players. The dyad analysis was proposed for basketball (Schmidt, O'Brien, & Sysko, 1999) but was also developed for individual racket sports (Palut & Zanone, 2005). Years later, they were also used to measure team sports (Passos et al., 2008; Yue et al., 2008). While some authors continued with dyad analysis, Schoöllhorn (2003) proposed a triad analysis consisting of a) a covered area by several or all players, b) a common center of gravity of several or all team members, and c) a geometric shape which several or all team members form. Therefore, this analysis method revealed that all changes in spatial parameters over time provided fruitful information about the behavior of a team as a whole (Schöllhorn, 2003). However, this line of research was not further developed until 2008 (Yue et al., 2008). From this year on, supported by technological development, several published studies have appeared on this topic,

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and many variables of spatial positioning tracking in team sports have been analyzed to measure tactical behavior (Low et al., 2020; Rico-González et al., 2020).

Several collective tactical variables have been classified into three geometric primitives (i.e., point, distance, and polygon) (Rico-González et al., 2020). Among other tactical variables, the *Centroid (i.e., represented as a point)*, also named the geometrical center (Yue et al., 2008) or center of gravity (Schöllhorn, 2003; Travassos et al., 2012) of the team and TA (total area) *surface area*, i.e., represented as a polygon has been commonly measured to assess tactical behavior in team sports (Low et al., 2020). The Centroid represents, in a single variable, the relative positioning of each team in forward-backward and side-to-side movements (Araújo & Davids, 2016). The change in centroid position (CCP) is the distance in meters between two consecutive measured points of the Centroid as the mid-point of the polygon. The TA represents the total field coverage of each team (Frencken & Lemmink, 2009) and is habitually used along with the Centroid to assess team behavior in team sports (Barnabé et al., 2016; Frencken et al., 2011; Frencken & Lemmink, 2009; Palucci Vieira et al., 2018). TA is defined as the total square meters of a polygon described by players as its vertex point. It is also used to assess inter-team coordination through the measurement of coupling stretch, relative phase (Lames, Ertmer, & Walter, 2010; Silva et al., 2014), and *pressure* index if compared to the team's centroids distance (Frencken & Lemmink, 2009). This variable expresses the relationship between the tactical shapes adopted and spaces exploited by both teams to support analysis of how they vary over time (Barnabé et al., 2016). In addition, it has been used as a *pressure* index (Frencken et al., 2011; Frencken & Lemmink, 2009). Furthermore, it has been suggested that increasing TA for the attacking sub-groups is important to destabilize the opposing team and create shooting opportunities (Duarte et al., 2012).

These variables are based on positional data (Rico-González et al., 2020). Currently, FIFA collectively labels various competing tracking technologies that differ in their methods or protocols as Electronic Performance and Tracking Systems (EPTS). Using EPTS, one of the parameters that researchers can modify according to their needs is the sampling rate of data collected per second, called "raw data" and expressed in hertz (Hz) (Winter, 2009). Among other factors, the sample rate capacity, which varies between EPTS technologies (Malone et al., 2017; Rico-González et al., 2020), influences the accuracy of the reported position of individual players on the pitch (Duarte et al., 2010; Frencken et al., 2010; Leser et al., 2011) and, consequently, the accuracy of team behavior variables (Rico-González et al., 2020). Deciding before the investigation which sampling frequency is to be used when recording the data (i.e., raw data) is fundamental to avoid violating the Nyquist sampling theorem. The theorem shows that the sampling frequency must be at least twice as high as the highest frequency given by the signal itself (i.e., if the amount of Hz is too low, errors or bias will occur in the recording) (Winter, 2009). However, when the sampling frequency is too high, noise may distort the signal, which increases linearly with frequency (Winter, 2009). In this sense, lowpass digital filtering of noisy signals has been an important procedure because the objective of any filtering technique is to attenuate noise and leave the true signal unaffected and stable (Winter, 2009). Once recorded, the data can go through data reduction using algorithms, producing software-derived data (Malone et al., 2017).

To date, it is unclear what sampling frequency is suitable to measure collective tactical behavior in team sports (Rico-González et al., 2020). The most commonly used sampling frequencies ranged from 0.4 to 100 Hz, from 0.4 to 50 Hz, and from 1 to 30 Hz to measure the GC, the distance between two points, and the area, respectively (Rico-González et al., 2020). Since the magnitude of the tactical behavior variables differs according to their characteristics (i.e., a single point or occupied space), we hypothesized that different sampling frequencies are needed according to the magnitude of the variable to be measured. In fact, Rico-González et al. (2020) proposed a set of standard items to assess the quality of the methodology, and one of these criteria suggested using different sampling rates for each variable. However, to our knowledge, no study has assessed the impact of the sampling frequency on the outcomes of tactical behavior variables during controlled tasks. Therefore, the study aimed to assess the impact of the sampling frequency on the measurement of collective tactical behavior (i.e., CCP and the TA).

METHOD

Participants

Data was collected from sixteen young male soccer players (under 16 years) (age 15.6 ± 0.8, height 1.70 ± 0.1 cm, weight 65.6 ± 10.2 kg) who belonged to the Torre Pacheco Soccer School (Spain). These players also participated in the cadet category of the Autonomous League of the Murcia region during the 2018-2019 season. The team's staff gave their consent for their participation in this study. Their legal guardians signed a written consent, and players consented to participate. The study, which was conducted according to the Declaration of Helsinki (2013), was approved by the Bioethics Commission of the University (Reg. Code 67/2017).

Procedure

Two teams of eight players participated in the exercises on a field of 30x40 meters (Coutinho et al., 2019). They were asked to execute three different controlled tasks: i) players walked for 1 minute along the line that described the perimeter of the area arranged (see Figure 1a), ii) players walked along the perimeter line, and after the coach's signal they ran to the center of a smaller area placed in the middle of the total area and then scattered towards the perimeter line again continuously for one minute (see Figure 1b), and iii) players walked along the perimeter line, and after the coach's signal they ran to the corners of a smaller area placed in the middle of the total area and then scattered towards the perimeter line again continuously for one minute (see Figure 1c).

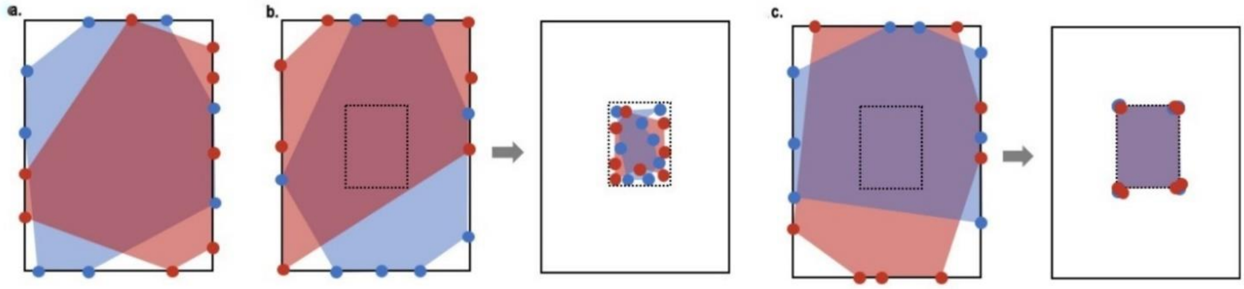

Figure 1. Representation of a) Task 1, b) Task 2, and c) Task 3. The total area is represented as yellow and black polygons, with players in the same colors defining an area as vertexes.

Data collection

Positional data were collected using a commercial EPTS (WIMU PRO™, RealTrack Systems, Almeria, Spain). Each device contains a 10 Hz GPS and an 18 Hz UWB (Ultra-wideband), as well as other sensors (three 3-axis gyroscopes, a 3-axis magnetometer, four 3-axis accelerometers, etc.), for data collection TA (m^2) and CCP (m), was measured at 18 Hz for raw data by radio ultra-wideband (UWB) sensor. The UWB system is composed of two sub-systems: (1) the reference system and (2) the devices tracked (carried by the players). The first comprises six antennae transmitters and receivers of the radio-frequency signals. The antennae (mainly the master antenna) computerize the position of the devices in the play area. In contrast, the devices receive that calculation (Bastida-Castillo et al., 2019). The TDOA algorithm was used to estimate positioning. The UWB occupies a very large frequency band (i.e., at least 0.5 GHz), unlike traditional radio communications operating on much smaller frequency bands (Alarifi et al., 2016). On the other hand, UWB is only allowed to transmit at very low power. Its signal emits little noise and can coexist with other services without influencing them (Granero-Gil et al., 2021). This UWB system has recently been validated for collective tactical behavior variables (Bastida-Castillo et al., 2019).

Ultra-wideband antennas were placed around the playing field. The auto-start process was carried out, followed by their synchronization before placing the tracking devices on the participants. The auto-start process followed a protocol that incorporated each device in the initial internal configuration. For auto-start, three aspects were considered: (i) leaving the device immobile for 30 seconds, (ii) placing it on a flat area, and (iii) not having magnetic devices around it. All WIMUs were attached to the players by a special vest inside a pocket placed between the scapulae at the T2-T4 level and before in-field exercises following previous study protocols (Reche-Soto et al., 2019).

Data processing

To investigate the accuracy of the UWB system for monitoring players' positions on the court, the data were transformed into raw position data (x and y coordinates) using software (S PRO, RealTrack Sytems, Almeria, Spain). Four different sampling frequencies were considered (1 Hz, 2 Hz, 4 Hz, and 10 Hz). And then, the x and y coordinate data of the UWB system were introduced and compared. Subsequently, we assessed the impact of the sampling frequency on the measurement of the CCP and TA. For statistical analysis purposes, the datasets corresponding to each sampling frequency were balanced to perform intraclass correlation coefficient and Bland Altman agreement. Balancing was performed, downsampling each dataset and calculating the data mean for each 2 Hz, 4 Hz, and 10 Hz value to have the same data in each dataset.

Statistical analysis

The data are presented as means with standard deviation. The Shapiro-Wilk test was applied to confirm the normality of the data, verifying the feasibility of using parametric inference. Following previous study principles (Kottner & Streiner, 2011; Zaki et al., 2012), we analyzed the agreement among the different sampling frequencies. We used these tests: 1) intraclass correlation coefficient (ICC) with a mixed two-way model and a 95% CI; 2) 2) one sample t-test of the differences using the Martin and Altman (1987) method to assess bias and agreement, 3) r-Pearson to explore the linear correlation between the different sampling frequencies; 4) t-test to explore significant differences between variable sampling frequency. Moreover, the magnitude of the difference was assessed using Cohen's *d* effect size (Cohen, 1988), qualitatively rated as follows: < 0.2 *trivial*, 0.2-0.6 *small*, 0.6-1.2 *moderate*, 1.2-2 *large*, and 2.0-4.0 *very large* (Hopkins et al., 2009). Statistical differences were considered significant if p< 0.05. Statistical analyses were developed using SPSS, and Figures were drawn using Graph Prism software.

RESULTS AND DISCUSSION

Results

ICC and linear correlation values ranged from 0.07 to 0.79 and from 0.49 to 0.99, respectively, according to the sampling frequencies (i.e., 1 Hz, 2 Hz, 4 Hz, and 10 Hz) and the task. Significant (p<0.01) and substantial (ES = *large*) differences were found among the CCP values recorded at different sampling frequencies in all tasks (Table 1).

Table 1. *Intra-class Correlation Coefficient, Linear Correlation, and mean comparison of the change in centroid position (CCP) by the sampling frequency*

Task	Variable	Sampling frequencies	N	*ICC*	*95% IC*	*BIAS*	*95%IC*	*r* (*p*-value)	*t* (*p*-value)	Cohen *d* *(rating)*
Task 1	Change in Centroid (m)	10vs4	300	0.33	0.22; 0.43	-0.18	-0.57; 0.21	0.49 (< 0.01)	-15.07 (< 0.01)	-1.27, *large*
		10vs2	300	0.18	0.07; 0.3	-0.49	-1.33; 0.84	0.49 (< 0.01)	-19.2 (< 0.01)	-1.63, *large*
		10vs1	300	0.1	-0.02; 0.21	- 01.11	-2.85; 0.63;	0.5 (< 0.01)	-20.77 (< 0.01)	-1.76, *large*
		4vs2	300	0.79	0.75; 0.83	-0.31	-0.76; 0.14	0.99 (< 0.01)	-21.89 (< 0.01)	-1.85, *large*
		4vs1	300	0.46	0.36; 0.55	-0.93	-2.32; 0.46	0.98 (< 0.01)	-21.82 (< 0.01)	-1.85, *large*
		2vs1	300	0.79	0.74; 0.83	-0.62	-1.56; 0.32	0.99 (< 0.01)	-21.57 (< 0.01)	-1.83, *large*

Task	Variable	Sampling frequencies	N	*ICC*	*95% IC*	*BIAS*	*95%IC*	*r* (*p*-value)	*t* (*p*-value)	Cohen *d* *(rating)*
Task 2	Change in Centroid (m)	10vs4	300	0.69	0.62; 0.76	-0.09	-0.2; 0.02	0.96 (< 0.01)	-19.58 (< 0.01)	-1.66, *large*
		10vs2	300	0.34	0.21; 0.45	-0.24	-0.53; 0.07	0.82 (< 0.01)	-18.85 (< 0.01)	-1.6, *large*
		10vs1	300	0.15	0.02; 0.28	-0.52	-1.21; 0.17	0.72 (< 0.01)	-18.73 (< 0.01)	-1.59, *large*
		4vs2	300	0.65	0.57; 0.73	-0.15	-0.4; 0.1	0.82 (< 0.01)	-14.99 (< 0.01)	-1.27, *large*
		4vs1	300	0.37	0.25; 0.48	-0.43	-1.04; 0.18	0.79 (< 0.01)	-17.59 (< 0.01)	-1.49, *large*
		2vs1	300	0.42	0.3; 0.52	-0.27	-0.89; 0.35	0.52 (< 0.01)	-10.85 (< 0.01)	-0.92, *moderate*
Task 3	Change in Centroid (m)	10vs4	300	0.49	-0.055; 0.75	-0.081	-0.19; 0.03	0.98 (< 0.01)	-21.46 (< 0.01)	-1.82, *large*
		10vs2	300	0.20	-0.07; 0.43	-0.21	-0.51; 0.09	0.92 (< 0.01)	-21.13 (< 0.01)	-1.79, *large*
		10vs1	300	0.07	-0.04; 0.18	-0.45	-1.16; 0.26	0.66 (< 0.01)	-19.59 (< 0.01)	-1.66, *large*
		4vs2	300	0.61	0.003; 0.83	-0.13	-0.31; 0.05	0.96 (< 0.01)	-20.46 (< 0.01)	-1.73, *large*
		4vs1	300	0.21	-0.04; 0.42	-0.37	-1; 0.26	0.73 (< 0.01)	-18.02 (< 0.01)	-1.53, *large*
		2vs1	300	0.54	0.12; 0.75	-0.24	-0.71; 0.23	0.85 (< 0.01)	-15.23 (< 0.01)	-1.29, *large*

Hz: Hertz; M: metres; p: p value; r: Pearson r; t: t test; %: percentage

High-to-perfect ICCs (0.91-1) and *high-to-perfect* linear correlations (r= 0.961-1; p < 0.01) were found among the TA values obtained through all sampling frequencies added (i.e., 1 Hz, 2 Hz, 4 Hz, and 10 Hz) derived from the software in the three tasks. No significant (p> 0.05) and substantial (ES = *trivial*) differences were found among the TA values obtained with all sampling frequencies in all tasks (Table 2).

Table 2. Intra-class Correlation Coefficient, Linear Correlation, and mean comparison of total area (TA) by sampling frequency

Task	Variable	Sampling frequencies	N	*ICC*	*95% IC*	*BIAS*	*95%IC*	*r* (*p*-value)	*t* (*p*-value)	Cohen *d* (*rating*)
Task 1	Total area (m²)	10vs4	300	0.96	0.95; 0.97	2.61	131.18; 125.97	0.96 (< 0.01)	0.66 (=507)	0.06, *trivial*
		10vs2	300	0.96	0.95; 0.97	2.7	130.35; 124.95	0.96 (< 0.01)	0.69 (=.489)	0.06, *trivial*
		10vs1	300	0.96	0.95, 0.97	3.71	125.54; 119.18	0.96 (< 0.01)	0.82 (=.411)	0.07, *trivial*
		4vs2	300	1	1; 1	0.09	6.4; 6.22	1 (< 0.01)	0.48 (=.635)	0.04, *trivial*
		4vs1	300	0.99	0.99; 0.99	0.57	22.19; 21.05	0.99 (< 0.01)	0.86 (=.389)	0.07, *trivial*
		2vs1	300	0.99	0.99; 0.99	0.47	15.25; 14.29	0.99 (< 0.01)	0.91 (=.362)	0.08, *trivial*
Task 2	Total area (m²)	10vs4	300	1	1; 1	-47	-11.34; 10.4	1 (< 0.01)	-1.09 (=.278)	-0.09, *trivial*
		10vs2	300	0.99	0.99; 0.99	462.3	107.73; 1032	0.998 (< 0.01)	0.12 (=.907)	0.01, *trivial*
		10vs1	300	0.993	0.99; 0.99	453.7	120.4; 1028	0.993 (< 0.01)	-1.11 (=.267)	-0.09, *trivial*
		4vs2	300	0.99	0.99; 0.99	0.66	-42.9; 44.24	0.997 (< 0.01)	0.38 (=.708)	0.03, *trivial*
		4vs1	300	0.99	0.99; 0.99	-2.51	-58.7; 53.68	0.995 (< 0.01)	-1.12 (=.266)	-0.09, *trivial*
		2vs1	300	0.99	0.99; 0.99	-3.19	-90.83; 84.45	0.988 (< 0.01)	-0.90 (=.369)	-0.08, *trivial*
Task 3	Total area (m²)	10vs4	300	1	1; 1	-0.05	-4.92; 4.82	1 (< 0.01)	-0.3 (=.765)	-0.03, *trivial*
		10vs2	300	0.99	0.99; 0.99	-0.13	-13.1; 12.84	0.99 (< 0.01)	-0.29 (=.769)	-0.03, *trivial*
		10vs1	300	0.99	0.99; 0.99	-0.41	-29.88; 29.06	0.99 (< 0.01)	-0.42 (=.674)	-0.04, *trivial*
		4vs2	300	0.99	0.99; 0.99	-0.36	-8.51; 7.79	0.99 (< 0.01)	-0.29 (=.772)	-0.03, *trivial*

Task	Variable	Sampling frequencies	N	*ICC*	*95% IC*	*BIAS*	*95%IC*	*r* (*p*-value)	*t* (*p*-value)	Cohen *d* *(rating)*
		4vs1	300	0.99	0.99; 0.99	-0.36	-25.01; 24.29	0.99 (< 0.01)	-0.45 (=.657)	-0.04, *trivial*
		2vs1	300	0.99	0.99; 0.99	-0.28	-16.87; 16.31	0.99 (< 0.01)	-0.52 (=.605)	-0.04, *trivial*

Hz: hertz; M²: square metres; p: p value; r: Pearson r; t: t test; %: percentage

For example, Figure 2 shows the CCP and TA values for each sampling frequency (i.e., 1 Hz, 2 Hz, 4 Hz, and 10 Hz) in Task 1.

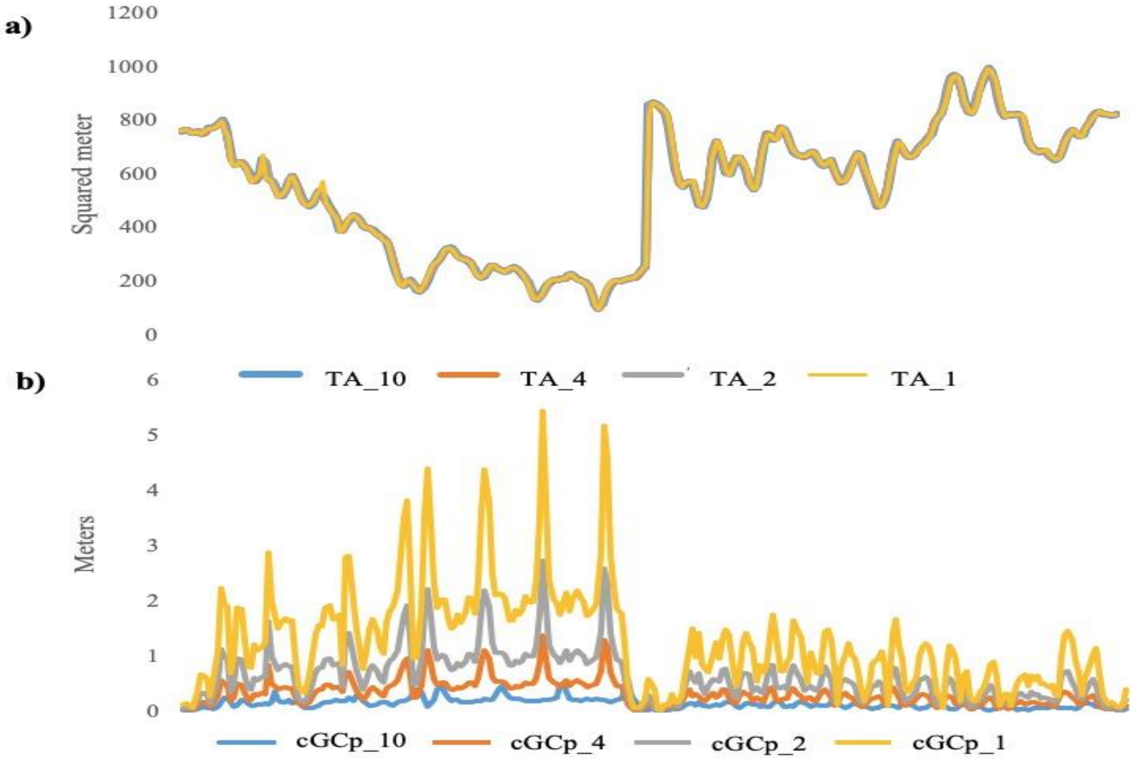

Figure 2. Mean representation of a) total area and b) change in centroid position (i.e., Task 1). TA= Total Area, CCP= Change in Centroid Position.

Discussion

To our knowledge, no study has assessed the influence of the sampling frequency on the measurement of tactical positioning variables in team sports. For this reason, the present study aimed to assess how the sampling frequency (i.e., 1 Hz, 2 Hz, 4 Hz, and 10 Hz) affected the outcomes of the CCP and TA during tactical analysis in sports. We found significant and large differences between the values of CCP measured at different sampling frequencies. However, we did not find significant differences between TA values measured at different sampling frequencies during three controlled tasks. These results suggested that the sampling frequency could indeed affect the outcomes of tactical positioning variables, requiring different sampling frequencies for each variable.

Significant and large differences, from 0.07 to 0.79 ICC values and 0.49 to 0.99 association values, respectively, were found between the CCP values measured at different sampling frequencies (i.e., 1 Hz, 2 Hz, 4 Hz, and 10 Hz) during the three controlled tasks (Table 1 and 2). This suggested that the CCP values in the three controlled tasks depended on the sampling frequency. Furthermore, at low frequencies, it obscured relevant data. A few years ago, Duarte et al. (2010) compared an original data set with different cut-off frequencies (3-Hz and 6-Hz) of an attacker's locomotion to determine what sampling frequency is more adequate for their main analysis (1 vs. 1 football sub-phase). They found less variation using a higher sampling frequency (6 Hz vs 3 Hz). So, it seems that the variable represented by a single point (a single pair of spatial coordinates), where the magnitude and the minimum time to change substantially may be lower than other collective tactical variables, such as total area, could be more sensitive to the sampling frequency.

On the contrary, we found only trivial differences between TA values measured at different sampling frequencies (i.e., 1 Hz, 2 Hz, 4 Hz, and 10 Hz) during the three controlled tasks (Table 2). The high to perfect ICC values and linear association suggested that adding just 1 Hz is sufficient to accurately measure TA in these tasks. Each team sport's structural traits and training tasks considerably affect the magnitude of TA (Clemente et al., 2013; Frencken et al., 2011; Timmerman et al., 2017) and the time to change substantially. Therefore, in further studies, the impact of the frequencies on TA values should be expanded to several team sports and training drills. If the results of these future studies were similar, less data would be helpful in the practical setting where a rapid evaluation of training/competition loads is necessary to assess performance and inform exercise prescription (Malone et al., 2017).

Positional data for collective analyses has become an important topic in team sports analysis (Low et al., 2020; Rico-González et al., 2020). Usually, researchers apply the same sampling frequency to measure all tactical variables in their studies (Rico-González et al., 2020). Moreover, coaches and technical staff should not consider the same sampling frequencies to assess all tactical variables (Rico-González et al., 2020). This can result in a loss of relevant data for some tactical variables (e.g., CCP in this study) but, simultaneously, an excessive amount of data to measure others (e.g., TA). In the case of CCP, one would lose relevant data. In the TA case, the excessive data could delay the report's analysis, resulting in difficulty responding to a complex calendar requiring rapid performance analysis (Malone et al., 2017).

CONCLUSION

The sampling frequency (i.e., 1 Hz, 2 Hz, 4 Hz, and 10 Hz) does not affect the measurement of the total area during tactical behavior analysis. Still, it does significantly affect the change in centroid position measurement. Thus, even though more studies are necessary, we recommend using different sampling frequencies to measure each tactical variable (i.e., total area and distance of Centroid) in team sports. Considering 1 Hz is enough to accurately measure the total area, while 10 Hz is suggested for the change in centroid position.

AUTHOR CONTRIBUTION STATEMENT

MRG and ALA led the writing of the manuscript. CDG and DPO developed the training program, coordinated the research lab, and collected data. DRV participated in data analysis and Proofread the papers. All authors read and approved the final draft article.

REFERENCES

Alarifi, A., Al-Salman, A., Alsaleh, M., Alnafessah, A., Al-Hadhrami, S., Al-Ammar, M., & Al-Khalifa, H. (2016). Ultra wideband indoor positioning technologies: Analysis and recent advances. Sensors, *16*(5), 707. https://doi.org/10.3390/s16050707

Araújo, D., & Davids, K. (2016). Team synergies in sport: Theory and measures. Frontiers in Psychology, *7*, 1-13. https://doi.org/10.3389/fpsyg.2016.01449

Barnabé, L., Volossovitch, A., Duarte, R., Ferreira, A. P., & Davids, K. (2016). Age-related effects of practice experience on collective behaviours of football players in small-sided games. Human Movement Science, *48*, 74-81. https://doi.org/10.1016/j.humov.2016.04.007

Bastida-Castillo, A., Gómez-Carmona, C. D., De La Cruz Sánchez, E., & Pino-Ortega, J. (2019). Comparing accuracy between global positioning systems and ultra-wideband-based position tracking systems used for tactical analyses in soccer. European Journal of Sport Science, *19*(9), 1157-1165. https://doi.org/10.1080/17461391.2019.1584248

Clemente, M. F., Couceiro, S. M., Martins, F. M. L., Mendes, R., & Figueiredo, A. J. (2013). Measuring collective behaviour in football teams: Inspecting the impact of each half of the match on ball possession. International Journal of Performance Analysis in Sport, *13*(3), 678-689. https://doi.org/10.1080/24748668.2013.11868680

Cohen, J. (1988). Statistical power analysis for the behavioral sciences. (Second Edition). L. Erlbaum Associates.

Coutinho, D., Gonçalves, B., Travassos, B., Abade, E., Wong, D. P., & Sampaio, J. (2019). Effects of pitch spatial references on players' positioning and physical performances during football small-sided games. Journal of Sports Sciences, *37*(7), 741-747. https://doi.org/10.1080/02640414.2018.1523671

Duarte, R., Araújo, D., Fernandes, O., Fonseca, C., Correia, V., Gazimba, V., Travassos, B., Esteves, P., Vilar, L., & Lopes, J. (2010). Capturing complex human behaviors in representative sports contexts with a single camera. Medicina, *46*(6), 408. https://doi.org/10.3390/medicina46060057

Duarte, R., Araújo, D., Freire, L., Folgado, H., Fernandes, O., & Davids, K. (2012). Intra- and inter-group coordination patterns reveal collective behaviors of football players near the scoring zone. Human Movement Science, *31*(6), 1639-1651. https://doi.org/10.1016/j.humov.2012.03.001

Frencken, W. G. P., Lemmink, K. A. P. M., & Delleman, N. J. (2010). Soccer-specific accuracy and validity of the local position measurement (LPM) system. Journal of Science and Medicine in Sport, *13*(6), 641-645. https://doi.org/10.1016/j.jsams.2010.04.003

Frencken, W, K. L., & Lemmink, K. (2008). Team kinematics of small-sided soccer games: A systematic approach. In: Reilly, T, and F. Korkusuz (Eds.), Science and Football VI. In Science and Football VI (pp. 161-166).

Frencken, W., Lemmink, K., Delleman, N., & Visscher, C. (2011). Oscillations of centroid position and surface area of soccer teams in small-sided games. European Journal of Sport Science, *11*(4), 215-223. https://doi.org/10.1080/17461391.2010.499967

Granero-Gil, P., Bastida-Castillo, A., Rojas-Valverde, D., Gómez-Carmona, C. D., de la Cruz Sánchez, E., & Pino-Ortega, J. (2021). Accuracy, inter-unit reliability and comparison between GPS and UWB-based tracking systems for measuring centripetal force during curvilinear locomotion. Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology, *235*(3), 237-248. https://doi.org/10.1177/1754337120961601

Hopkins, W. G., Marshall, S. W., Batterham, A. M., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. Medicine and Science in Sports and Exercise, *41*(1), 3-13. https://doi.org/10.1249/MSS.0b013e31818cb278

Kottner, J., & Streiner, D. L. (2011). The difference between reliability and agreement. Journal of Clinical Epidemiology, *64*(6), 701-702. https://doi.org/10.1016/j.jclinepi.2010.12.001

Lames, M., Ertmer, J., & Walter, F., L. (2010). Oscillations in football-Order and disorder in spatial interactions between the two teams. International Journal of Sport Psychology, *41*(4), 85.

Leser, R., Baca, A., & Ogris, G. (2011). Local positioning systems in (game) sports. Sensors, *11*(10), 9778-9797. https://doi.org/10.3390/s111009778

Low, B, Coutinho, D, Gonçalves, B, Rein, R, Memmert, D, & Sampaio, J. (2020). A systematic review of collective tactical behaviours in football using positional data. *50*, 343-385. https://doi.org/10.1007/s40279-019-01194-7

Malone, J. J., Lovell, R., Varley, M. C., & Coutts, A. J. (2017). Unpacking the black box: Applications and considerations for using gps devices in sport. International Journal of Sports Physiology and Performance, *12* (Suppl 2), 18-26. https://doi.org/10.1123/ijspp.2016-0236

Martin Bland, J., & Altman, D. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. The Lancet, *327*(8476), 307-310. https://doi.org/10.1016/S0140-6736(86)90837-8

Palucci Vieira, L. H., Aquino, R., Moura, F. A., Barros, R. M. L. de, Arpini, V. M., Oliveira, L. P., Bedo, B. L. S., & Santiago, P. R. P. (2018). Team dynamics, running, and skill-related performances of brazilian u11 to professional soccer players during official matches. Journal of Strength and Conditioning Research, *33*(8), 2202-2216. https://doi.org/10.1519/JSC.0000000000002577

Palut, Y., & Zanone, P.-G. (2005). A dynamical analysis of tennis: Concepts and data. Journal of Sports Sciences, *23*(10), 1021-1032. https://doi.org/10.1080/02640410400021682

Passos, P., Araújo, D., Davids, K., Gouveia, L., Milho, J., & Serpa, S. (2008). Information-governing dynamics of attacker-defender interactions in youth rugby union. Journal of Sports Sciences, *26*(13), 1421-1429. https://doi.org/10.1080/02640410802208986

Reche-Soto, P., Cardona-Nieto, D., Diaz-Suarez, A., Bastida-Castillo, A., Gomez-Carmona, C., Garcia-Rubio, J., & Pino-Ortega, J. (2019). Player load and metabolic power dynamics as load quantifiers in soccer. Journal of Human Kinetics, *69*, 259-269. https://doi.org/10.2478/hukin-2018-0072

Rico-González, M., Los Arcos, A., Rojas-Valverde, D., Clemente, F. M., & Pino-Ortega, J. (2020). A survey to assess the quality of the data obtained by radio-frequency technologies and microelectromechanical systems to measure external workload and collective behavior variables in team sports. Sensors, *20*(8), 2271. https://doi.org/10.3390/s20082271

Rico-González, M., Los Arcos, A., Nakamura, F. Y., Moura, F. A., & Pino-Ortega, J. (2020). The use of technology and sampling frequency to measure variables of tactical positioning in team sports: A systematic review. Research in Sports Medicine, *28*(2), 279-292. https://doi.org/10.1080/15438627.2019.1660879

Rico-González, M., Pino-Ortega, J., Nakamura, F. Y., Moura, F. A., & Los Arcos, A. (2020). Identification, Computational Examination, Critical Assessment and Future Considerations of Distance Variables to Assess Collective Tactical Behaviour in Team Invasion Sports by Positional Data: A Systematic Review. International Journal of Environmental Research and Public Health, *17*(6), 1952. https://doi.org/10.3390/ijerph17061952

Schmidt, R. C., O' Brien, B., & Sysko, R. (1970). Self organization of between person cooperative tasks and possible applications to sport. International Journal of Sport Psychology, *30*(4), 558-579.

Schöllhorn. (2003). Coordination Dynamics and its Consequences on Sports. Int. J. Comp. Sci. Sport.

Silva, P., Duarte, R., Sampaio, J., Aguiar, P., Davids, K., Araújo, D., & Garganta, J. (2014). Field dimension and skill level constrain team tactical behaviours in small-sided and conditioned games in football. Journal of Sports Sciences, *32*(20), 1888-1896. https://doi.org/10.1080/02640414.2014.961950

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

Travassos, B., Araújo, D., Duarte, R., & McGarry, T. (2012). Spatiotemporal coordination patterns in futsal (indoor football) are guided by informational game constraints. Human Movement Science, *31*(4), 932-945. https://doi.org/10.1016/j.humov.2011.10.004

Winter, D. A. (2009). Biomechanics and motor control of human movement (4. ed). John Wiley & Sons, Inc., Hoboken, New Jersey. https://doi.org/10.1002/9780470549148

Yue, Z., Broich, H., Seifriz, F., & Mester, J. (2008). Mathematical Analysis of a Soccer Game. Part I: Individual and Collective Behaviors. Studies in Applied Mathematics, *121*(3), 223-243. https://doi.org/10.1111/j.1467-9590.2008.00413.x

Zaki, R., Bulgiba, A., Ismail, R., & Ismail, N. A. (2012). Statistical Methods Used to Test for Agreement of Medical Instruments Measuring Continuous Variables in Method Comparison Studies: A Systematic Review. PLoS ONE, *7*(5), e37908. https://doi.org/10.1371/journal.pone.0037908