Measurement 201 (2022) 111666

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

Validity and reliability of NOTCH® inertial sensors for measuring elbow joint angle during tennis forehand at different sampling frequencies

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A R T I C L E I N F O

Keywords:
IMU
Motion capture
3D joint kinematics
Racket sports
Multi-sensor fusion

A B S T R A C T

Portable and low-cost motion capture systems are gaining importance for biomechanical analysis. The aim was to determine the concurrent validity and reliability of the NOTCH® inertial sensors to measure the elbow angle during tennis forehand at different sampling frequencies (100, 250 and 500 Hz), using an optical capture system with sub-millimetre accuracy as a reference. 15 competitive players performed forehands wearing NOTCH and an upper body marker-set and the signals from both systems were adjusted and synchronized. The error magnitude was tolerable (5-10°) for all joint-axis and sampling frequencies, increasing significantly at 100 Hz for the flexion–extension and pronation-supination angles ($p = 0.002$ and 0.023; Cohen $d > 0.8$). Concordance correlation coefficient was very large (0.7–0.9) in all cases. The within-subject error variation between the test–retest did not show significant differences ($p > 0.05$). NOTCH® is a valid, reliable and portable alternative to measure elbow angles during tennis forehand.

1. Introduction

Inertial measurement units (IMUs) are sensors used commonly in medical rehabilitation, performance and kinematics analysis in sports [1,2]. In tennis, the use of this type of technology has become increasingly frequent [3], since it is an economical and portable alternative that allows to estimate kinematic parameters such as the body segments' orientation, position and joint angles [4–6], the energy transition between segments during the strokes [7] or the ball speed based on a racket-mounted motion sensor [8]. All this makes IMUs suitable to collect data in a natural environment and perform in-field tennis biomechanical analyses, which provide more valid results than laboratory tests [9].

Optical motion capture systems (OS) are the gold standard for measuring kinematics parameters, and are widely used in sport sciences and tennis studies [10]. In fact, these systems have been improved over the last two decades and the measurement error of current OS systems is<0.5 mm [11]. Despite the fact that OS have been proven to be accurate tools to analyse sport kinematics [11], using them outside the laboratory is an added difficulty [12]. The increase in costs and the complexity of the data processing reduce the extent of this approach in actual field applications. Thus, for example, to evaluate the hitting kinematics of a tennis forehand on an indoor tennis court [13], set up a system of 8 infrared cameras, which is not a viable solution for many research institutes. OS systems also involve precise and time-consuming marker placement. The simplest OS based model to assess elbow kinematics –which could be measured using only two IMUs, one on the arm and other on the forearm– are based on 5 reflective markers [13–14]. For this reason, validation of more portable systems, such as IMUs or wearable ultrawideband transceivers mounted on body segments [15], is necessary to be able to evaluate tennis players in real-game situations [9]. Another alternative could be mocap markerless systems [16–18] but they still have the problem of complicated assembly and are difficult to use in conditions where player occlusion can occur.

IMUs usually contain three different types of sensors: magnetometer, accelerometer and gyroscope. Joint kinematics is computed by the use *sensor fusion algorithm,* combining accelerometer and magnetometer measurements with gyroscope measurements [19]. From this, it follows that the algorithm will only work properly if all three sensors are capable of measuring the full range of accelerations and angular

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https://doi.org/10.1016/j.measurement.2022.111666
Received 17 January 2022; Received in revised form 25 June 2022; Accepted 21 July 2022
Available online 30 July 2022

velocities (in the particular case of the accelerometer and gyroscope). This is not a concern in the case of slow-motion gestures such as walking or moving arms to bring an object but in ballistic and explosive skills, such as tennis strokes involving high rotational velocities, it could be a problem. The sensors have proven to be valid and reliable even in sports activities such as football [20] or swimming [21]. These studies have established a good agreement and tolerable values for the root mean square error (between 5° and 10°) for measuring upper limbs kinematics, since the differences in the magnitude of the error can be attributed to biomechanical models and different calibration methods [22]. Upper limbs angular velocities in tennis strokes – such as arm internal rotations or wrist flexion movements – sometimes exceed 2000 degrees per second [23], and most of the commercial sensors are limited to this range. For this reason, and especially in this case, sensors capable of capturing higher angular velocities are needed. Only two studies have been found that have evaluated the validity and reliability of the sensors in tennis strokes. One of them evaluates the accuracy of the gyroscopes [24], while the other evaluates the accuracy of the sensors Xsens® MVN system for measuring 3D joint angles [25]. Xsens® MVN system proved to be valid to measure the kinematics of the arm for the majority of the variables analyses, but not for the elbow joint angle in transverse plane [25]. There are also other recent studies that analyse the validity of an IMU system to measure the kinematics of ballistic gestures, but these works do not analyses the kinematics of the upper limbs, which is where the highest angular velocities are reached. For example, Harnett et al., [26] analyse the validity of some IMUs to study the kinematics of the knee, pelvis and trunk in the case of cricket and find no statistically significant differences with the reference system for the trunk lateral bending and knee flexion. The IMUs that has been proposed to be validated in this study (NOTCH®) only has only been previously validated during functional daily task movements [27]. Despite previous validation studies, until now, there is scarce literature for the accuracy of the IMUs for measuring explosive upper limbs movements involving high rotational velocities and large ranges of movements, such as the tennis forehand.

The upper limbs kinematics of the tennis forehand is crucial to achieve high performance in tennis, as it contributes to achieve greater ball velocity [28,29], ball spin [30] or higher stroke accuracy [10,31]. For example, Pedro et al. [6] conclude that the extension movement of the elbow is the second largest contributor to racket speed, after the horizontal flexion of the upper arm around the shoulder joint. Genovois et al., [30] indicate that during the backswing and forward swing of a topspin forehand, the forearm is more extended than during a flat forehand drive. In the impact and the follow-through, the elbow flexion and forearm pronation are also more pronounced in the topspin forehand drive [30]. In the case of table tennis, inertial sensors allowed to differentiate the kinematics of the upper segments between able-bodied and wheelchair-bound players during forehand and backhand strokes [32,33]. In addition to improving the performance-related biomechanical factors, the implementation of these sensors for the upper limbs kinematics analysis could aid to assess the risk of musculoskeletal injury, considering that inefficient joint actions can increase the risk of injury [34]. For example, there is a relation between hitting technique and elbow epicondylitis [35], a common tennis injury, and IMUs could serve to prevent the mechanical load on the elbow from being excessively high [36].

Sampling means taking a certain number of samples every second from a continuous analog signal [37]. Sampling frequency (i.e. the amount of data collected per second) is something that has traditionally concerned researcher in the field [38–39]. From a theoretical overview, the optimal sample rate should be calculated following the Nyquist–-Shannon sampling theorem which states that, under suitable assumptions, in an analog-to-digital conversion the minimum sampling frequency necessary to avoid ambiguity and loss of information (e.g., aliasing) in the reconstruction of the original analog signal is equal to twice its maximum frequency [37]. From an operational point of view instrumental sampling frequency is usually selected by using a reference system and assessing the error trade-off of the signal in relation to the sampling rates [38–39]. There are no studies that analyse the influence of the sampling frequency on the accuracy of the IMUs for measure kinematics variables in the particular case of tennis [40]. In this vein, some authors suggest that 200 Hz is the recommended sampling rate needed to analyse the kinematics in tennis strokes [41], but this issue has not been analysed in depth. In fact, IMU validation studies in tennis have used a single sampling frequency, which coincide with the maximum sampling range of the devices evaluated. For example, Pedro et al., [25] analysed the Xsens® MVN system at 240 Hz or Delgado-García et al., [24] analysed the Nexgen® Ergonomic system at 128 Hz (Table 1). NOTCH® inertial sensors have not yet been evaluated, although their price and features make them ideal for use in tennis. In fact, some companies have already used them to design software to evaluate batting or swinging technique (4dmotionsports.com). If the researcher wants to make long-time recordings (such as a complete tennis match), it seems more convenient to use lower sampling frequencies so as not to saturate the memory of the devices and to be able to use popular mathematics software, limited from a computational point of view, such as Microsoft Excel. In other words, lower sampling rates would result in a lower data load, longer battery life, and higher efficiency of data processing [42]. Similarly, it would be interesting to use higher sampling frequencies to see if the error decreases akin to other gestures of a ballistic nature [39]. On this line low sampling frequencies could lead to missing peaks or spikes, a signal distortion and finally in a loss of information [39].

The aim was to determine the concurrent validity and reliability (within-subject error variation) of the NOTCH® inertial sensors to measure elbow joint angle during tennis forehand at different sampling frequencies (100 Hz, 250 Hz and 500 Hz), by comparing data with a OS (gold standard, 500 Hz) in a sample of competitive tennis players. Based

Table 1
Feature comparisons between NOTCH® and other IMUs presenting validation studies in tennis.

	NOTCH®	Xsens® MVN	Nexgen® I2M
Reference of the validation study	–	[18]	[19]
Approximate cost of the system used in the study	<500 USD	>3.5 K USD	>10 K USD
Sampling frequency*1 (Hz)	500 Hz	240 Hz	128 Hz
Accelerometer maximum range (g)	± 32	± 16	± 6
Gyroscope maximum range (°/s)	± 4000	± 2000	± 2000
Magnetometer maximum range (Gauss)	± 16	± 8	± 6
Experimental conditions	–	Laboratory	Laboratory
Optical system used as reference criterion system	–	Qualisys AB	Optitrack (Natural Point)
Number of participants included	–	18	4
Level of expertise of participants	–	Experienced and intermediate	Beginner and competitive
Stroke analysed	–	Forehand	All
Number of strokes analysed per participant	–	3	100
Kinematic variable studied	–	Joint angle	Sensor angular velocity
Error reported relative to the reference (RMSE)	–	1.5–13.1°/s	4.4–35.4°/s
Reliability outcome	–	–	0.41–0.58°/s*2

*1 Refers to the maximum sampling frequency (in the case of the Notch) or the one used in the validity study in the case of the IMU Xsens® MVN and Nexgen® I2M systems.
*2 In this case, the reliability was studied by rotating the sensors on the same axis, not in tennis hits.
RMSE: Root Mean Square Error

on previous research, we hypothesise that NOTCH® is a low-cost and portable alternative (< $500 USD) that includes all instrumentation and data processing for measuring elbow joints angles in tennis forehand. Considering that there is a relationship between a proper technique and injuries, the confirmation of this hypothesis could help sport scientists measure upper limb kinematics and mechanical loads as well as prevent the appearance of tennis injuries, such as the tennis elbow, during field-based experimentation. Studying the validity and reliability of NOTCH® inertial sensors is also necessary to know if they are suitable for programming specific software for the evaluation of sport technique in the case of tennis.

2. Methods

2.1. Participants

Data were collected from 15 healthy players (all male) with experience in regional competitions. The anthropometric characteristics of the participants were as follows: mean (SD); age 22.4 (6.5) years; height 177.3 (5.5) cm; weight 75.4 (6.2) kg; BMI 21.1 (1.8) Kg/m^2. According to the International Tennis Federation classification, 10 players had an international tennis number of between 2 and 3 (advanced tennis players), and five players had an international tennis number of 4 [43]. All participants met the inclusion criteria: (1) to have the license form the National Tennis Federation and (2) to not suffer any injuries within the 6 months prior to the data collection. After receiving detailed information on the objectives and procedures of the study, each subject signed an informed consent form in order to participate, in compliance with the ethical standards of the World Medical Association's Declaration of Helsinki (2013). It was made clear that the participants were free to leave the study if they saw fit. The study was approved by the Institutional Review Board.

2.2. Procedures

Participants were individually tested within one day. First, the anthropometric characteristics (weight [kg], body fat [%] and height [cm]) were measured using a bioimpedance meter (Inbody 230, Inbody Seoul, Korea) and a precision stadiometer (SECA 222, SECA Corp., Hamburg, Germany). All measurements were taken with the participants wearing underwear.

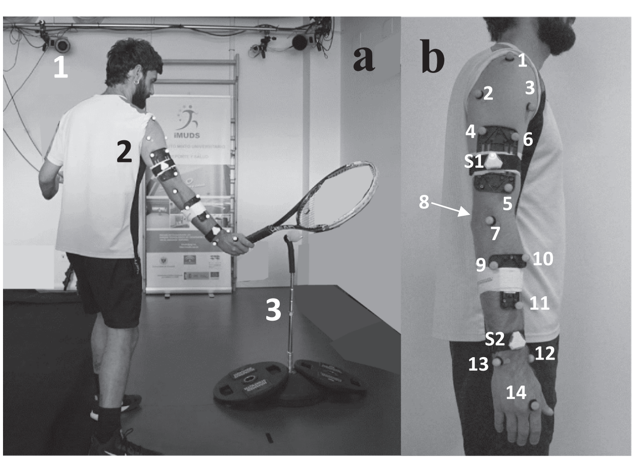

Fig. 1. Set up of the experiment (a) indicating the infrared camera model used, the biomechanics marker set and the pendulum ball that the player should hit. The biomechanical markers used (b): (1) *Acromion*; (2) back of the *humeral head*; (3) front of the *humeral head*; (4–6) cluster of the arm; (7) lateral *epicondyle*; (8) medial *epicondyle*; (9–11) cluster of the forearm; (12) *radius styloid process;* (13) *ulna styloid process*. S1 is the IMU sensor located in the arm and S2 is the IMU sensor located in the forearm.

Two IMUs and retroreflective markers (eight anatomical markers and two clusters) were affixed on the dominant arm of the tennis players (Fig. 1), according to the University of Western Australia's upper body marker set with an extensive use in sport science and tennis studies [23,44]. Subsequently, the players performed the hitting test, using their own racket. They performed six series of 10 forehand recordings with the IMUs at 100 Hz, 250 Hz, and 500 Hz. Two series were recorded at each sampling frequency in order to analyse the reliability of the IMUs (within-subject error variation). The OS was recorded simultaneously at 500 Hz. All forehands performed in the study were carried out by hitting a pendulum ball (Fig. 1).

2.3. Data collection

The elbow joint angle during tennis forehand was measured under laboratory conditions using the NOTCH® IMU system and OS (Qualisys®, Gothenburg, Sweden) with submillimetre accuracy [11]. Flexion and extension angles (Fle/Ext [°]), corresponding to the sagittal plane of the elbow and pronation and supination angles (Pron/Sup [°]), corresponding to the transverse plane of the elbow were measured. The following lines explain in detail the characteristics of the IMUs and OS devices and the data collection:

- NOTCH® IMUs system (Wearnotch, Notch Interfaces, Inc., New Jersey, USA): It is a wireless IMU-based system embedded with nine-axis inertial sensors (three-axis gyroscope, three-axis accelerometer, three-axis magnetometer), with a maximum range of measurement of $\pm$ 32 g, $\pm$ 4000°/s and a maximum sampling rate of 500 Hz (Table 1). The system has been previously validated through functional daily task movements [27]. The elbow joint angles from the NOTCH® system were downloaded, thanks to an extended license (which costs $50 USD per year). Static and dynamic sensor calibrations were conducted with the purpose to ensure their optimal performance. A 'steady pose' (anatomical position) was collected prior to each forehand measured, The steady pose was used to capture the orientation of the arm, and thus the NOTCH® IMUs algorithms joined it to a predefined skeleton pose. The IMU was mounted in a rigid plastic case attached to manufacturer-made straps, which were positioned in the segments of the participant. Elbow joint angles measured during all forehands performed during the study were transferred from the NOTCH® Pioneer application to an Android device (Nokia 6.1., Espoo, Finland) via Bluetooth, and then to a server computer for their analysis. Additionally, NOTCH® uses proprietary sensor fusion, filtering methods, and algorithms to calculate joint angles that are restricted for the user.
- Qualisys® optoelectronic system (Qualisys®, Gothenburg, Sweden) consists of nine infrared high-speed cameras (Oqus 300, Qualisys, Sweden), alongside which the Qualisys Track Manager (version 2.17, Qualisys, Gothenburg, Sweden) software was used. All forehands performed during the study were recorded at a sampling frequency of 500 Hz, and the data were down-sampled to 100 Hz, 250 Hz and 500 Hz to compare the signals with that of the IMUs. An upright static trial was used to create the upper limbs segment (i.e., arm and forearm) and the joint centres (i.e., elbow) posteriorly used in the motion trials. To avoid the brightness disturbances that could be confused with the retroreflective markers, care was taken with the lighting conditions. A calibration wand manufactured by Qualisys® was used for spatial calibration, following the manufacturer's guidelines. The calibration was repeated until obtaining the best possible calibration parameters (the average residuals of the cameras being below 0.4 mm).

2.4. Signal processing and filtering

The 3D marker trajectories during the standing position and forehand drive trials were identified by the OS system and exported to C3D format in the Qualisys Track Manager. Then, using the Visual 3D software (V6, C-motion, Inc. Germantown, USA), and based on the University of Western Australia's upper body marker set, the positions and orientations of the dominant arm and forearm were reconstructed and used to compute the elbow joint angles (flexion/extension and pronation/supination). Two different Cardan sequences (AP-AXIAL-ML and ML-AP-AXIAL) were used to calculate pronation-supination and flexion–extension (the motive underlying this relevant decision is explained in the document provided as supplementary material). The elbow joint angle was then filtered forward and backward through an 18 Hz second-order Butterworth filter to obtain the result of a zero-lag fourth-order filter. To select the cut-off frequency of the said filter, an analysis of the residuals was previously carried out [45] using an Excel ad-hoc tool. Based on previous literature [46], every frequency between 1 Hz and 32 Hz at 1 Hz intervals was tested. Residuals (RMSE) were plotted against a cut-off frequency, and a straight line of the best fit was projected back to the y-axis from the linear portion of the residual-frequency curve. A horizontal line was then extended from the vertical-intercept back to the residual-frequency curve, and the frequency at which the two lines meet was chosen as the optimal cut-off frequency [47]. This was done for each subject, and the rounded mean (without decimal places) of the cut-off frequency was considered (18 Hz). Finally, elbow joint angles (Fle/Ext and Pron/Sup) from the IMUs and OS were synchronised using an Excel spreadsheet, using a cross-correlation based phase shift technique [20]. This procedure of synchronising signals has been used previously in studies to analyse the validity of biomechanical analysis instruments [20,48]. This type of synchronisation was chosen given the impossibility of conducting it via electrical pulse (start/stop). The angles from the IMUs were processed unfiltered, as the interest of the study is to analyse the data directly provided by the devices, without any additional data processing. Despite the above, the NOTCH® signal had to be slightly transformed, based on the aforementioned cross-correlation technique, in order to compare it with the OS signal. This transformation is better explained in a document that is added as supplementary material.

2.5. Statistical analysis

Descriptive statistics are represented as mean and standard deviation (SD). Tests of normal distribution and homogeneity, determined by the Shapiro–Wilk and Levene's tests, respectively, were conducted on all data prior to analysis. In order to determine the validity of the system regarding the reference system (IMUs vs OS), the linear relationship and level of agreement between both signals (IMUs vs OS) were evaluated using Lin's concordance correlation coefficient (Lin's CCC) [49], with a high Lin's CCC indicating the absence of systematic error difference between measurements [50]. The following criteria were adopted to interpret the magnitude of correlations between measurement variables: < 0.1 (trivial), 0.1–0.3 (small), 0.3–0.5 (moderate), 0.5–0.7 (large), 0.7–0.9 (very large) and 0.9–1.0 (almost perfect) [51]. The magnitude of the error was also quantified by calculating the root mean square error (RMSE) between the two motion capture systems. The RMSE interpretation was based on a previous study [52] as follows: good (RMSE $\leq 2^\circ$), acceptable ($2^\circ <$ RMSE $\leq 5^\circ$), tolerable ($5^\circ <$ RMSE ≤ 10) and unbearable accuracy (RMSE > 10). For comparing the error of measurement (RMSE) at different sampling rates (100 Hz vs 250 Hz vs 500 Hz), one-way repeated measures ANOVA followed by Bonferroni multiple post-hoc comparison tests were carried out. To evaluate the reliability of the sensors of the elbow, a student's *t*-test for dependent samples was conducted, considering the RMSE and Lin's CCC in the two measurements (test–retest), at each sampling frequency (within-subject error variation). The magnitude of the differences was interpreted using the Cohen's d effect size (ES) (between-group differences) [53] and reported as follows: trivial (<0.2), small (0.2–0.49), medium (0.5–0.79), and large (≥ 0.8) [53]. All data analyses were performed using Excel 2016 and Real Statistic Using Excel Packages [54,55], and the level of significance used was $p < 0.05$.

3. Results

Fig. 2 shows two examples of the elbow joint angle obtained using the IMUs superimposed on the one obtained with the OS – one for the flexion/extension and another for the pronation/supination.

3.1. Validity

Table 2 shows a comparative analysis (RMSE and Lin's CCC) between IMUs and OS elbow joint angles at different sampling frequencies (100 Hz, 250 Hz and 500 Hz) during tennis forehand. All the comparisons showed a tolerable RMSE (RMSE < 10). Relative to the correlation analysis (Lin's CCC), very large correlations ($r > 0.81$) were obtained in all associations between both systems.

3.2. Differences in the error of measurement as a function of sampling frequency

Repeated measures ANOVA showed differences between the RMSE at different sampling frequencies ($p = 0.0024$), and the Bonferroni post-hoc analysis showed no significant differences when comparing 100 Hz vs 250 Hz, 250 Hz vs 500 Hz or in flexion/extension nor pronation/supination ($p > 0.05$) (Table 3). Instead, significant differences were found between 100 Hz and 500 Hz in flexion/extension ($p = 0.001$) and pronation/supination ($p = 0.023$), with a large effect size (≥ 0.8) in both cases (Table 4).

3.3. Reliability

The comparative analyses of the RMSE between the test–retest at different sampling frequencies, and in the two anatomical movements analysed showed no significant differences ($p > 0.05$) in any case (Table 4). This indicates that the error was consistent between measurements. Regarding the Lin's CCC between devices, it always remained above 0.8, and no significant differences ($p > 0.05$) were found between the test–retest or in any comparisons.

4. Discussion

The aim of the present study was to analyse the concurrent validity and reliability of a IMUs system for measuring the elbow joint angle during forehand strokes, comparing the data against an OS (gold standard). The RMSE of the transformed signal was tolerable ($5^\circ <$ RMSE $\leq$ 10) for all anatomical movements and sampling frequencies. The Lin's CCC between both devices was very large (0.7–0.9) in all cases. The RMSE increased significantly ($p > 0.05$) in the recordings made at 100 Hz as compared to those made at 500 Hz, for both planes of the elbow (flexion/extension and pronation/supination), with a large effect size (≥ 0.8) in both planes. The within-subject error variation between test–retest showed no significant differences in any of the elbow planes and sampling frequencies used, and the level of agreement also remained > 0.8 in all cases.

Previous studies [22,25] have suggested that a RMSE below 10° demonstrates very good accuracy of the IMU devices. The error of measurement of the IMUs were below this threshold for the two planes of the elbow and all the sampling frequencies used. If we compare the results with those of studies that have analysed IMU validity, we will find similar values for the agreement and RMSE scores, relative to the upper limb kinematics. For example, Fantozzi et al. [21] found RMSE of 15° and 10° in the sagittal and transverse planes of the elbow while swimming, whereas Barreto et al. [56] found similar correlation coefficients and RMSE in the elbow during gymnastics skills. Tennis strokes have a particular idiosyncrasy as they are usually executed at a high-speeds, thereby achieving high angular velocities, especially in the last segments of the kinetic chain (that is, at the elbow and at the wrist). For this reason, validation studies of the specific IMUs for this sport

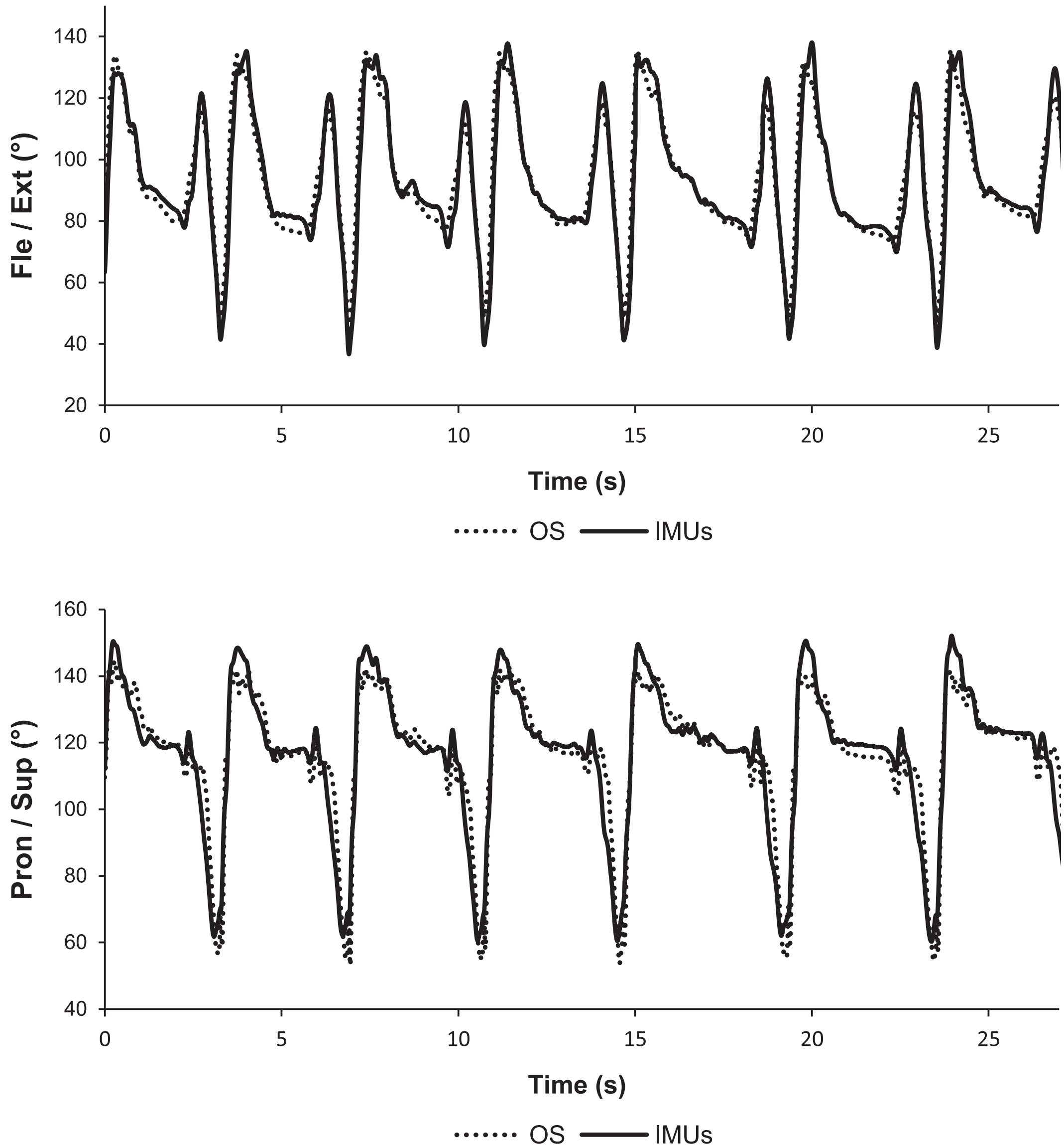

Fig. 2. Elbow joint angles during tennis forehand obtained from the OS and IMUs synchronised at 500 Hz of one of the study participants.

Table 2
RMSE and Lin's CCC between elbow joint angles (Fle/Ext and Pron/Sup) obtained from IMUs and OS during tennis forehand at different sampling frequencies (100 Hz, 250 Hz and 500 Hz).

Sample Frequency	Elbow joint angle	RMSE*	Lińs CCC*
100 Hz	Fle/Ext	8.66°	0.81
	Pron/Sup	8.53°	0.83
250 Hz	Fle/Ext	7.53°	0.85
	Pron/Sup	7.66°	0.86
500 Hz	Fle/Ext	5.76°	0.89
	Pron/Sup	6.66°	0.86

* RMSE: Root Mean Square Error; Lińs CCC: Lińs Concordance Correlation Coefficient.

Table 3
Bonferroni post-hoc test (from repeated measures ANOVA) between elbow joints angles obtained at the different sampling frequencies.

Condition	Mean RMSE (°) (SD)	p-value*	ES*
Fle/Ext 100 Hz vs Fle/Ext 250 Hz	8.78 (1.67) vs 7.27 (1.94)	0.266	0.62
Fle/Ext 100 Hz vs Fle/Ext 500 Hz	8.78 (1.67) vs 5.77 (1.79)	**0.001***	**1.54**
Fle/Ext 250 Hz vs Fle/Ext 500 Hz	7.27 (1.94) vs 5.77 (1.79)	0.068	0.91
Pron/Sup 100 Hz vs Pron/Sup 250 Hz	8.41 (1.89) vs 7.67 (1.15)	0.508	0.48
Pron/Sup 100 Hz vs Pron/Sup 500 Hz	8.41 (1.89) vs 6.67 (1.61)	**0.023***	**1.23**
Pron/Sup 250 Hz vs Pron/Sup 500 Hz	7.67 (1.15) vs 6.67 (1.61)	0.204	0.75

* p-value: significant differences for values lower than 0.05; *ES: Effect size (D-Cohen).

should be carried out, especially considering that the speed could affect the accuracy of the measurement [24]. A similar study [25] analysing IMU accuracy while performing tennis forehands reported a Lin's CCC > 0.9 and a RMSE below 2° in the sagittal plane of the elbow (flexion/extension), only slightly better than the present investigation. In contrast, for the elbow pronation-supination angle, data from the present work (Table 2) showed a higher level of agreement and a lower

Table 4
Comparison of the RMSE and Lin's CCC between test–retest at different sampling rate and in different anatomical movements (Fle/Ext and Pron/Sup).

Sample rate	Elbow joint angle	RMSE (°) mean (SD)		p-value	Lin's CCC mean (SD)		p-value
		Test	Re-test		Test	Re-test	
100 Hz	Fle/Ext	8.78 (1.67)	9.14 (2.50)	0.48	0.81 (0.14)	0.81 (0.13)	0.75
	Pron/Sup	8.41 (1.89)	8.67 (1.92)	0.65	0.83 (0.06)	0.82 (0.08)	0.55
250 Hz	Fle/Ext	7.27 (1.94)	6.71 (1.49)	0.12	0.85 (0.1)	0.88 (0.07)	0.23
	Pron/Sup	7.67 (1.15)	7.58 (1.83)	0.86	0.86 (0.08)	0.87 (0.07)	0.69
500 Hz	Fle/Ext	5.77 (1.79)	6.06 (2.24)	0.71	0.89 (0.06)	0.86 (0.09)	0.24
	Pron/Sup	6.67 (1.61)	6.57 (1.37)	0.89	0.86 (0.07)	0.89 (0.06)	0.17

* p-value: significant differences for values lower than 0.05.

RMSE than in the study of Pedro et al. [25] (they reported Lin's CCC of 0.79 and RMSE of 13.1°). The differences in precision of the different IMUs evaluated could be predominantly attributed to the biomechanical models and different calibration methods [22]. The threshold beyond which the error will be considered large also depends on the objectives of the investigation. For example, [57] found differences of about 16° for the elbow flexion angle at impact between prepubescent's and adults. This value is higher than the error of measurement (RMSE) of the NOTCH® sensors, thus concluding that this device is sufficiently accurate to detect the differences in this particular case. On the other hand, [13] found differences between elite- and high-performance players below one degree for the elbow flexion angle during the forehand strokes, probably requiring, in this case, a more accurate system.

In the present study, it was found that the error (measured as RMSE) increased significantly ($p < 0.05$), if we compare the recordings made at 100 Hz and 500 Hz. This result supports the hypothesis of previous studies [40,58] which indicate that a minimum sampling frequency of 200 Hz is required for an accurate upper limb's kinematic analysis of tennis strokes. Despite the differences found, the level of agreement and the magnitude of the error of the recordings made at 100 Hz were very large (0.8–0.9) and tolerable (RMSE $< 10°$) in all cases, with values similar to that of the literature [21,22]. Therefore, recording at 100 Hz with the present sensors could be appropriate when the researcher is interested in collect long recordings and wants to measure, for example, the physical load in a competition [59,60]. In this case, the sampling rate required does not have to be as high as when the main interest of the research is, for example, comparing the hitting kinematics between players of different levels of performance [10,13]. Finally the magnitude of the error remained constant ($p > 0.05$) throughout the course of the test–retest, and the level of agreement was > 0.8 in all planes of the elbow and sampling frequencies used, which indicates the reliability of the IMUs.

Summarising, NOTCH® IMUs could be an alternative (transforming the signal by using a simple linear equation) to other sensors that have been more tested in the scientific field and are supported by a large number of high-impact publications [25]. The sensors used in the present manuscript have three notable advantages over other models used for biomechanical analysis: I) low price, which allows laboratories with a limited budget to use them; II) the measurement range of gyroscopes (±4000 degrees per second) that allows evaluating ballistic gestures such as tennis strokes, where sometimes 2000°/s are exceeded [23]; III) their capability to measure at high sampling rates (500 Hz) which allow them to analyse tennis strokes in detail, and even capture the moment of the ball impact with the tennis racket. Another real use of these sensors would be the design and implementation of systems for the detection, classification and evaluation of strokes in real competition situations [61–64]. Finally, the NOTCH® sensor can be considered an economical and valuable tool for field-based experimentation.

Study limitations are associated with iron structures within laboratories that may interfere with electronic devices for data collection and the sample size used since it was not determined by statistical methods. Despite this, level of agreement between both measurement systems was strong, and the differences (measured as RMSE) seem small enough to detect differences in elbow angulations during tennis forehand. IMUs allow evaluating in natural playing conditions, something which, until recently, was difficult to do with traditional photogrammetric systems. Others limitations of the study is that the IMU and OS system signals could not be synchronised by electrical pulse and that the S2 and forearm marker cluster were not attached together. Therefore, we believe that work that analyses the validity of these devices in a controlled laboratory situation is very necessary and should be done before using them to evaluate the kinematics of hitting the field. Further research is required to check the validity and reliability of the NOCTH® measurements in different anatomical joints and strokes. Also, future studies could include other IMUs (e.g., Xsens) attached to the same location as NOTCH® (on top of each other), and the same analysis could be performed on both. This is because, obtaining RMSEs of $< 10°$ in a limited testing condition (limited number of trials, limited duration of the test, limited number of participants, limited type of motions) does not truly reveal the validity of the IMUs. However, given the errors of another well-established IMU, such as Xsens, a reader could understand the true potential of the NOTCH® sensors. Also, it would be important to conduct an independent study to validate the orientation measured with proprietary sensor fusion of NOTCH®. The characteristics of these sensors (high sampling frequency and high measurement ranges of the accelerometer, gyroscope and magnetometer) and the possibility of programming them via an API provided by the manufacturers (wearnotch.com) make them ideal for advanced biomechanics assessment in tennis.

5. Conclusions

This is the first study to analyse the validity of IMUs for measuring elbow joint angles by comparing data with an optoelectronic system, at different sampling frequencies during tennis forehand. The results indicate that the NOTCH® inertial measurements system is a valid and reliable tool to measure elbow joint angles during tennis forehand. Even though all sampling frequencies analysed (100 Hz, 200 Hz and 500 Hz) showed good validity and reliability scores, the best results were obtained at 500 fps, so it is recommended to use this sampling frequency for short recordings (wherein the memory or the computation time is not a concern). Finally, although a simple signal transformation must be applied before use, NOTCH® sensors can help develop and refine technical actions and to correct biomechanical inefficiencies. Also, the potential of a low-cost tool will be an aid for tennis coaches and sports science researchers, who have limited access to laboratory evaluations.

CRediT authorship contribution statement

Emilio J. Ruiz-Malagón: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Gabriel Delgado-García:** Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision. **Santiago Castro-Infantes:** Investigation, Resources, Data curation, Writing – review & editing. **Maximiliano Ritacco-Real:** Methodology, Software, Formal analysis, Writing – review & editing, Visualization, Supervision. **Víctor M. Soto-Hermoso:** Methodology, Validation, Formal analysis, Writing – review & editing, Visualization, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgements

The authors would like to thank all those athletes who participated in this research. We declare that the study sponsors had no involvement in this study.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.measurement.2022.111666.

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