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Accelerometer validity during collisions

Abstract

Context: Accelerometer peak impact accelerations are being used to measure player physical demands in contact sports. However, their accuracy to do so has not been ascertained. **Purpose:** To compare peak impact acceleration data from an accelerometer contained within a wearable tracking device with a three dimensional motion analysis (MA) system during tackling and bumping. **Methods:** Twenty-five semi-elite rugby athletes wore a tracking device containing a 100 Hz triaxial accelerometer (MininmaxX S4, Catapult Innovations, Australia). A single retro-reflective marker was attached to the device with its position recorded by a 12-camera MA system during three physical collision movements (tackle bag, bump pad and tackle drill; n = 625). The accuracy, effect size, agreement, precision and relative errors for each comparison were obtained as measures of accelerometer validity. **Results:** Physical collision peak impact accelerations recorded by the accelerometer overestimated (mean bias 0.60 *g*) those recorded by the MA system ($P < 0.01$). Filtering the raw data at a 20 Hz cut-off improved the accelerometer's relationship with MA data (mean bias 0.01 *g*; $P > 0.05$). When considering the data in nine magnitude bands, the strongest relationship with the MA system was found in the 3.0 *g* or less band and the precision of the accelerometer tended to reduce as the magnitude of impact acceleration increased. Of the three movements performed, the tackle bag movement displayed the greatest validity with MA. **Conclusions:** The findings indicate that the MinimaxX S4 accelerometer can accurately measure physical collision peak impact accelerations when data were filtered at a 20 Hz cut-off frequency. As a result, accelerometers may be useful to measure physical collisions in contact sports. **Keywords:** *Acceleration, motion analysis, impact, load, intensity.*

Introduction

Physical collisions form a major component of contact team sports and include movements such as tackling, bumping, and landing on the ground [1,2]. These physical collisions have been shown to expose athletes to an increased risk of contact related injury [1,3]. Further, the intensity of the collision may contribute to the incidence of injury [3,4]. Historically, collisions have been identified retrospectively using video replay [5,6]. However, this approach is limited largely due to test-retest reliability issues [7], and the considerable time required to collect and analyse the data [8].

Commercially-available wearable tracking devices have been developed for field team sports (e.g., MinimaxX S4, Catapult Innovations, Australia) and are worn by athletes on their upper back in a sports vest [9]. Such devices typically contain global positioning system (GPS), gyroscope and magnetometer sensors [10]. They also contain an accelerometer, making it possible to measure the accelerations associated with sporting movements, including physical collisions in contact sports [9,11,12]. As acceleration is directly proportional to external force [13], accelerometers can therefore be used to reflect the intensity of collisions that athletes experience.

Previous research has shown that accelerometers can be used to describe physical collisions during game-play [2,9]. Additionally, research assessing the intensity of collisions have found strong relationships between accelerometer data and subjective categorisation from video observation [11,12]. These studies show accelerometers have the potential to quantify physical collisions in contact sports, however in order for accelerometers to be used with confidence for these purposes, the data output should be both reliable and valid.

To this end, Boyd et al. [14] assessed the reliability of the MinimaxX S4 accelerometer and found a good level of within- and between-device reliability (0.9% to 1.9%). The concurrent-validity (a type of criterion-related validity where a new instrument [i.e., accelerometer] is compared to an alternative form of measurement previously validated [15]) of an accelerometer (SPI Pro, GPSports Pty Ltd., Australia) during jumping, landing [16], running and change of direction movements [17,18] has also been assessed. In both studies, raw accelerometer data overestimated force plate-derived ground reaction force, although the application of a low-pass filter improved the validity of the data. A more recent investigation assessed the concurrent validity of another accelerometer (MinimaxX S4, Catapult Innovations, Australia) using a three-dimensional motion analysis (MA) system during treadmill walking, jogging and running [18]. Similarly, the raw accelerometer data overestimated the concurrent measure and filtering improved the validity of the data.

As seen from this previous research, two accelerometer types have been assessed, targeting lower intensity movements and displaying consistent overestimations of movement intensity. In contact sports, high intensity collisions are of more interest to coaches than low intensity collisions due to the additional physical demand these larger collisions place on the body [4,12]. However, no study has validated the MinimaxX S4 accelerometer at intensities similar to those experienced in contact sports (e.g., >5.0 *g* [11,19]). The aim of this study was to concurrently validate peak impact acceleration data from an accelerometer contained within a MinimaxX S4 wearable tracking device with a MA system during tackling and bumping.

Methods

Subjects

Twenty-five males (age 23.3 ± 4.3 years; height 1.80 ± 0.06 m; mass 96.5 ± 18.1 kg; mean ± SD) competing in the Victorian Rugby Union Premier Division were recruited for participation in the study. Ethics approval for the study was provided by the relevant human research ethics committee, with written informed consent obtained from all participants prior to testing.

Design

This study evaluated the concurrent validity of peak impact acceleration data collected from an accelerometer against a MA system during physical collisions movements. Raw accelerometer data as well as data filtered at several cut-off frequencies were compared.

Methodology

Participants wore a single, wearable tracking device (MinimaxX S4, Catapult Innovations, Australia) in a sports vest, which contained a 100 Hz triaxial accelerometer [9]. The device weighed 67 grams and was 88 × 50 × 19 mm in dimension. To assess the concurrent validity of the accelerometer, a single five gram, 13 mm retro-reflective marker was affixed with medical tape to the wearable tracking device and its position was tracked using a 12-camera, MA system (Raptor-E, Motion Analysis Corporation, USA) operating at 500 Hz. The MA system was calibrated both statically (L-frame) and dynamically (0.5 m wand; to 0.50004 ± 0.0005 m [mean ± SD] and a precision of 0.00006 m). In clinical gait analysis, MA systems are the gold standard measure used to accurately describe the kinematics of motion [20]. Recently, MA systems have been used in sports laboratories to assess the concurrent validity of wearable tracking device sensors (e.g., [18,21,22]).

Familiarisation with all equipment and procedures, as well as a standardised warm-up was performed prior to commencing data collection. Participants then performed three physical collision tasks outdoors on a rugby field, during which time acceleration and three-dimensional kinematic data were collected. The cameras comprising the MA system contain new proprietary image processing software that enables outdoor (in direct sunlight) and indoor capture. The three physical collision tasks were broken down into those that involved ground contact (tackle bag) and those that involved body contact, as either the ball carrier being tackled (tackle drill) or the defender tackling the ball carrier (bump pad). The run up velocity (prior to collision) was self-selected with instruction given to run as fast as possible and perform each physical collision as is typical during game-play.

In the tackle bag task, participants started 5 m away from a stationary upright padded tackle bag (1.53 × 0.46 m, Senior Tackle Dummy, Madison Sport, Australia) and ran and tackled the tackle bag to the ground. In the bump pad task, participants performed the same running movement, however a second participant was standing stationary six meters away and prior to contact was instructed to forcefully step into the approaching participant while holding a padded hit shield (0.76 × 0.51 m, Large Hit Shield, Madison Sport, Australia). Lastly, in the tackle drill task, both participants started 10 m apart and ran at each other, with the first designated as the defender and the second designated as the ball carrier (peak impact acceleration of interest). The defending participant was instructed to tackle the first participant around their centre of gravity (i.e., aiming for shoulder contact around the midriff area). Participants were matched for mass and after five trials, swapped roles. Participants were required to perform 10 trials of the bump pad (n = 250) and tackle bag tasks (n = 250) and five trials of the tackle drill task (n = 125), in the same order as mentioned above (this order was chosen to expose participants to the two tasks that involved some form of padding prior to the tackle drill task which did not). A one minute break was given between each trial with an additional five minutes recovery given between each task. The trial was excluded if a trial was performed unsuccessfully (e.g., missed or broke through a tackle too easily etc.), and the participants were reminded of correct technique (see Gabbett [23]) and asked to repeat the trial.

In addition, no direction was given in regards to the footwear worn (either football boots or cross-trainers) during testing.

Resultant data, defined as a single vector representing the combined effects of the X, Y and Z axes, for both the MA system and accelerometer were analysed through the manufacturer-supplied software (MA: Cortex, version 3.6.1.1315, Motion Analysis Corporation, USA; accelerometer: Logan Plus, version 5.0.9.2, Catapult Sports, Australia). Accelerometer-derived accelerations, which were corrected for gravity (Inertial Movement Analysis proprietary software, Catapult Sports, Australia), along with MA position data were then exported to Microsoft Excel™ for further analysis (version 14.0.6112.500, Microsoft Corporation, USA). Three-dimensional kinematic data are subject to high-frequency noise not the result of human movement [24,25]. For example, even in static conditions, reconstructed marker data are not stationary [24]. As a result, when estimating time derivatives, noise within the raw signal may be amplified [26,27]. For these and other reasons, marker position data are low-pass filtered [25], to remove high-frequency noise and obtain accurate derivative estimates [26,28]. To choose the optimal cut-off frequency, a residual analysis of the difference between the unfiltered and filtered MA signals over a range of cut-off frequencies was performed for each movement, with the decision made via visual inspection [27]. As a result of the residual analysis, MA data for all movements were filtered at a 10 Hz cut-off frequency. The MA smoothed X, Y and Z position data were then differentiated twice to calculate acceleration [29]. The resultant vector was then calculated in multiples of gravity or *g*. To investigate the effect different filtering cut-off frequencies had on accelerometer accuracy, the raw accelerometer data were filtered at multiple cut-off frequencies (30 Hz, 25 Hz, 20 Hz, 15 Hz, 10 Hz, 8 Hz and 6 Hz) and compared against the MA system. To filter both the MA and accelerometer data, a low-pass, zero-lag, 4th order Butterworth digital filter was applied in a customised Labview program (version 7.1, National Instruments, USA).

To synchronise the accelerometer and MA system, at the beginning of each trial the participant stood within the capture volume of the MA system and the wearable tracking device was hit from the side while being filmed by a digital video recorder (GZ-MG330HAA, JVC, Japan) operating at 50 Hz. The data were subsequently imported into video analysis software (Team Pro version 7, Dartfish Ltd, Switzerland) and the hit peak acceleration was used to synchronise the two devices. Thus, the time-point at which the physical collision occurred at was recorded and the peak impact acceleration value manually retrieved for each trial.

Statistical analysis

The accelerometer was examined across a broad range of peak impact accelerations from 2.2 - 14.5 *g*. Prior to undertaking the main statistical analyses, a Kruskal-Wallis test was performed to determine whether differences in mean bias values between the raw accelerometer data and concurrent measure existed between the 25 trials. As this analysis was exploratory in nature, the critical alpha level was set at 0.05. No differences for trial were noted, as such all data were pooled for all subsequent analyses.

In order to determine the ability of the accelerometer to quantify peak accelerations, multiple measurement indices of validity were obtained. The level of accuracy, effect size, agreement, precision and relative error for the accelerometer and MA accelerations were obtained by calculating the mean bias [30], Cohen's *d* , 95% limits of agreement (95% LoA [31]), RMSEP [30] and coefficient of variation (CV%) respectively.

Analysis of variance (ANOVA) was performed on four occasions, each analysing the data reported in different formats. To determine if peak acceleration values recorded by the accelerometer (eight levels: raw, filtered at 30 Hz, 25 Hz, 20 Hz, 15 Hz, 10 Hz, 8 Hz and 6 Hz) differed from the MA system, a one-way ANOVA was performed. Filtered accelerometer values displaying high levels of accuracy, agreement and precision with the MA system (e.g., mean bias and RMSEP values close to 0.0 *g*) were then used for all subsequent analyses. A second one-way ANOVA was performed in order to investigate whether differences in mean bias existed between the accelerometer and MA system when peak impact accelerations were compared across multiple magnitude bands (nine levels: <3.0 *g*, 3.0 *g* to 3.99 *g*, 4.0 *g* to 4.99 *g*, 5.0 *g*, 5.0 *g* to 5.99 *g*, 6.0 *g* to 6.99 *g*, 7.0 *g* to 7.99 *g*, 8.0 *g* to 9.99 *g* and 10.0 *g* or greater). These magnitude bands were modified from scaling categories previously reported in the literature [11,19]. A third one-way ANOVA was performed in order to investigate whether differences in mean bias existed between the accelerometer and MA system across the different movements undertaken (three levels: tackle bag, bump pad and tackle drill). Lastly, a fourth one-way ANOVA was performed in order to investigate whether peak impact accelerations could be used as a feature to distinguish between the three physical collisions performed (three levels: tackle bag, bump pad, tackle drill).

Bonferroni corrected pairwise comparisons for the four ANOVAs were used to identify the source of any differences, with the alpha level adjusted to 0.006, 0.006, 0.02 and 0.02 respectively via the Bonferroni procedure [32]. The exploratory analysis and ANOVAs were conducted using SPSS (version 21.0, IBM Corporation, USA). The mean bias, effect size, 95% LoA, RMSEP and CV were calculated using Microsoft Excel™.

Results

Indices of accuracy, effect size, agreement, precision and relative error between raw and filtered accelerometer data and the MA system are presented in Table 1. Raw and 30 Hz filtered accelerometer data significantly overestimated MA data ($P < 0.006$, mean bias = 0.34-0.60 *g*, Cohen's $d = 0.16$-0.28). Filtering raw accelerometer data at 25 Hz ($P = 0.41$, Cohen's $d = 0.10$), 20 Hz ($P = 1.00$, Cohen's $d = 0.01$) and 15 Hz ($P = 0.06$, Cohen's $d = -0.15$) cut-offs displayed better validity when compared with MA data (mean bias = 0.21 to -0.31). However, the lowest cut-offs (10 Hz, 8 Hz and 6 Hz) significantly underestimated MA data ($P < 0.006$, mean bias = -0.92 to -1.87 *g*, Cohen's $d = -0.47$ to -1.03). Filtering raw accelerometer data using a 20 Hz cut-off frequency demonstrated the best accuracy, agreement and precision values. Therefore, raw accelerometer data filtered at the 20 Hz cut-off frequency was used for all subsequent analyses.

** Insert Table 1, 2 and 3 roughly here **

Table 2 shows the relationship between the accelerometer data filtered at a 20 Hz cut-off frequency and the MA system for each magnitude band. The mean bias values calculated in the 9.0 *g* to 9.99 *g* magnitude band significantly underestimated those calculated in the <5.0 *g* and 6.0 *g* to 7.0 *g* magnitude bands ($P < 0.006$). The precision of the accelerometer tended to reduce as the magnitude of impact acceleration increased.

The mean bias values calculated for the tackle bag movement significantly underestimated those calculated for the bump pad and tackle drill movements ($P < 0.02$; Table 3). There was only a minor difference in mean bias between the tackle drill and bump pad movements. The tackle bag movement displayed the strongest agreement and precision, while the bump pad movement displayed the strongest accuracy with the MA system. The tackle bag peak accelerations were significantly greater than the tackle drill, with peak accelerations for both movements higher than the bump pad.

Discussion

The aim of this study was to concurrently validate peak impact acceleration data from an accelerometer with a MA system during three physical collision movements. When filtered at 20 Hz the accelerometer displayed the strongest relationship with the MA system (i.e., accuracy, agreement, precision etc.). However, raw and 30 Hz filtered accelerometer data overestimated, and 10 Hz, 8 Hz and 6 Hz accelerometer data underestimated, physical collision peak impact accelerations. Further, both the intensity of acceleration recorded and the type of physical collision performed influenced accelerometer validity. Collectively, these results highlight that accelerometers can be used to accurately quantify the intensity of physical collisions experienced in contact sports, provided that the raw data is filtered using an appropriate cut-off frequency (e.g., 20 Hz).

The raw accelerometer data overestimated physical collision peak impact accelerations (mean bias = 0.60 *g*), and displayed poor agreement and precision with MA peak accelerations. This finding is supported by previous research which has shown that the accelerometer contained within wearable tracking devices can overestimate concurrent methods by 15.6% to 30.8% [16-18]. For example, a physical collision with a true peak impact acceleration value of 6.0 *g* if recorded by the accelerometer will have an error of 1.24 *g* under or over the actual value when raw data are used.

The poor accuracy of these devices for assessing peak impact accelerations may be due to noise present in the raw accelerometer signal [33]. Noise refers to elements within the raw signal that are not a result of human movement and add characteristics (e.g., frequency content) to the true signal [27,34]. Filtering of a raw signal is commonly used to reduce noise [27,34]. Although the raw accelerometer data overestimated physical collision peak accelerations, when filtered at 30 Hz, 25 Hz, 20 Hz and 15 Hz cut-off frequencies, the validity with the MA system was improved (e.g., mean bias = -0.31 to 0.34 *g*, RMSEP = 0.75-0.94 *g*). The concurrent validity of the 20 Hz cut-off frequency was equal or superior to all other cut-offs assessed. Indeed, the accuracy (0.01 *g*), effect size (0.005), agreement (-1.46 to 1.48 *g*) and precision (0.75 *g*) values were superior to all other accelerometer cut-off frequencies trialled. However, the concurrent validity of the 10 Hz, 8 Hz and 6 Hz cut-off frequencies were equal or poorer to the raw data (e.g., RMSEP 1.23-2.19 *g*). When physical collision peak accelerations are filtered with a cut-off frequency at or below 15 Hz, the accelerometer data may be over-filtered, thereby underestimating the intensity of the collisions. While this was the case for the lower cut-off frequencies, the 20 Hz cut-off frequency appeared optimal, displaying the strongest concurrent validity with the MA system.

The findings of the current study are similar to previous research [16-18]. However, the optimal cut-off frequency was different, with two of the aforementioned studies suggesting a 10 Hz filter as optimal [17,18]. The difference in the optimal cut-off frequency between this study (20 Hz) and previous research may be due to the different movements performed, the wearable tracking devices assessed and/ or concurrent measure chosen (including differences in sampling rates). For instance, previous research suggests that the dominant frequencies of human movement increase with movement intensity [35,36]. Therefore, physical collisions may have higher frequency content characteristics than other contact sport movements (e.g. walking, running etc.) assessed by previous validation work. Caution is advised if filtering accelerometer accelerations below 20 Hz as this may underestimate physical collision peak impact accelerations, which are used to quantify the physical demands of sports performance[19]. When the 20 Hz filtered accelerometer data were split into nine magnitude bands and three activities, results showed strong concurrent validity between the accelerometer and MA system, with mean bias values not differing by more than 0.47 *g* and RMSEP not exceeding 1.0 *g*. Thus, considering the movements performed and the broad range of peak accelerations assessed, including those considerably larger than previously evaluated (range 0.3-6.0 *g* [16-18]), the results of this study support the accelerometer's ability to accurately measure the intensity of physical collisions in contact sports.

In addition, the peak accelerations recorded were different between the three activities performed. To this end, the detailed analysis of accelerometer peak impact accelerations, as a discriminatory feature, may be used to identify the type of physical collision performed [2,9]. Future research should consider the accuracy of the peak impact acceleration feature to identify and discriminate between contact sport movements (e.g., tackling, running, jumping etc.).

A limitation of this study was that the physical collisions assessed were simulated to represent game-play. Although in-game validation would be preferred, current validity measures are not suited to such analyses [37]. As a result, the peak accelerations recorded may be different than those recorded during game-play, which should be acknowledged. Another potential source of error is the moment arm of the reflective marker. As the reflective marker must be visible at all times the moment arm of the marker and accelerometer may be different.

Practical applications

The accelerometer can be confidently applied to measure the intensity of physical collisions when filtered at 20 Hz. As a result, accelerometers may be useful to measure physical collisions in contact sports. Given the limitations of other sensors within wearable tracking devices to measure physical collisions, accelerometers may provide a valuable tool for the regular monitoring of physical workloads during training and game-play. The detailed analysis of accelerometer data (e.g., individual and accumulated collisions) may help devise individual-specific training and recovery programs to improve performance and reduce injury risks. There is also the possibility that accelerometer peak accelerations may help classify the type of movement performed. However, this requires further investigation.

Conclusion

The results of this study suggest that the accelerometer sensor contained within MinimaxX S4 wearable tracking device technology can accurately measure physical collision peak accelerations when data are filtered at a 20 Hz cut-off frequency. With appropriate filtering, the accelerometer can be considered an acceptable objective method to quantify physical collisions in contact sports. Caution is advised, however when interpreting raw data, with the accelerometer output likely to overestimate the intensity of the physical collision. Detailed analysis of accelerometer data alone or in combination with other wearable sensor data may help practitioners better understand the physical demands imposed on athletes. Future research should continue to assess the validity of the accelerometer in-game or in simulated scenarios where multiple sporting movements are performed.

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Table 1 Data relating to accuracy, effect size, agreement, precision and relative error for each accelerometer variable assessed (n = 625).

Measure	Mean ± SD (*g*)	Cohen's *d*	Mean Bias ± SD (*g*)	95% LoA (*g*)	RMSEP (*g*)	CV (%)
MA	6.00 ± 2.22					
Raw	6.60 ± 2.10 [a]	0.28	0.60 ± 1.09	-1.53 to 2.73	1.24	15.1
30 Hz	6.34 ± 2.05	0.16	0.34 ± 0.88	-1.38 to 2.06	0.94	12.0
25 Hz	6.21 ± 2.04	0.10	0.21 ± 0.82	-1.40 to 1.81	0.84	10.8
20 Hz	6.01 ± 2.01	0.01	0.01 ± 0.75	-1.46 to 1.48	0.75	9.6
15 Hz	5.69 ± 1.95	-0.15	-0.31 ± 0.70	-1.69 to 1.07	0.77	9.5
10 Hz	5.08 ± 1.72 [a]	-0.47	-0.92 ± 0.82	-2.53 to 0.68	1.23	14.5
8 Hz	4.67 ± 1.55 [a]	-0.69	-1.33 ± 0.95	-3.19 to 0.53	1.63	19.3
6 Hz	4.13 ± 1.29 [a]	-1.03	-1.87 ± 1.14	-4.14 to 0.37	2.19	26.9

[a] The mean difference (accelerometer vs. MA) is significant at the 0.008 level;
CV – coefficient of variation; RMSEP - root mean square error of prediction; SD - standard deviation; 95% LoA – 95% limits of agreement.

Table 2 Data relating to accuracy, effect size, agreement, precision and relative error at each acceleration band, MA versus 20 Hz filtered acceleration data.

Acceleration band (*g*)	Mean Bias ± SD (*g*)	Cohen's *d*	95% LoA (*g*)	RMSEP (*g*)	CV (%)
<3.0 (n = 25)	0.08 ± 0.42	-0.20	-0.90 to 0.74	0.42	10.8
3.0-3.99 (n = 85)	-0.04 ± 0.53	-0.09	-1.07 to 0.99	0.53	9.9
4.0-4.99 (n = 101)	0.20 ± 0.62[a]	0.42	-1.03 to 1.42	0.58	11.7
5.0-5.99 (n = 123)	0.08 ± 0.73[a]	0.14	-1.35 to 1.51	0.73	9.8
6.0-6.99 (n = 107)	0.09 ± 0.74[a]	0.16	-1.37 to 1.55	0.75	8.9
7.0-7.99 (n = 74)	0.04 ± 0.86	0.06	-1.64 to 1.72	0.85	8.7
8.0-8.99 (n = 57)	-0.21 ± 0.92	-0.30	-2.02 to 1.60	0.94	8.8
9-9.99 (n = 35)	-0.47 ± 0.90	-0.28	-2.22 to 1.29	1.00	7.0
10.0+ (n = 19)	-0.17 ± 1.02	-0.14	-2.16 to 1.82	1.00	6.6

[a] The mean difference (accelerometer vs. MA) is significant at the 0.01 level when compared to the 9.0-9.99 *g* acceleration band;
CV – coefficient of variation; RMSEP - root mean square error of prediction; SD - standard deviation; 95% LoA – 95% limits of agreement.

Table 3 Data relating to accuracy, effect size, agreement, precision and relative error for each movement performed, MA versus 20 Hz filtered acceleration data.

Movement	Mean ± SD (*g*)	Mean Bias ± SD (*g*)	Cohen's *d*	95% LoA (*g*)	RMSEP (*g*)	CV (%)
Tackle bag (n = 250)	7.24 ± 1.65[b]	-0.28 ± 0.64[a]	-0.16	-1.52 to 0.97	0.69	6.5
Bump pad (n = 250)	4.79 ± 1.58[b]	0.20 ± 0.74	0.13	-1.24 to 1.64	0.76	11.3
Tackle drill (n = 125)	6.00 ± 1.93[b]	0.21 ± 0.82	0.10	-1.39 to 1.81	0.84	11.2

[a] The mean difference (accelerometer vs. MA) is significant at the 0.01 level when compared to bump pad and tackle drill movements;
[b] The mean difference (movement) is significant at the 0.01 level;
CV – coefficient of variation; RMSEP - root mean square error of prediction; SD - standard deviation; 95% LoA – 95% limits of agreement.