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Reliability and agreement of Azure Kinect and Kinect v2 depth sensors in the shoulder joint range of motion estimation

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Background: Depth sensor–based motion analysis systems are of interest to researchers with low cost, fast analysis capabilities, and portability; thus, their reliability is a matter of interest. Our study examined the agreement and reliability in estimating the basic shoulder movements of Azure Kinect, Microsoft's state-of-the-art depth sensor, and its predecessor, Kinect v2, by comparing them with the gold standard marker-based motion analysis system.
Methods: In our study, the shoulder joint ranges of motion of 20 healthy individuals were analyzed during dominant-side flexion, abduction, and rotation movements. The reliability and agreement between methods were evaluated using the intraclass correlation coefficient (ICC) and the Bland-Altman method.
Results: Compared to the gold standard method, the old- and new-generation Kinect showed similar performance in terms of reliability in the estimation of flexion (ICC = 0.86 vs. 0.82) and abduction (ICC = 0.78 vs. 0.79) movements, respectively. In contrast, the new-generation sensor showed higher reliability than its predecessor in internal (ICC = 0.49 vs. 0.75) and external rotation (ICC = 0.38 vs. 0.67) movement.
Conclusion: Compared to its predecessor, Kinect Azure has higher reliability in analyzing movements in a lower range and variability, thanks to its state-of-the-art hardware. However, the sensor should also be tested on multiaxial movements, such as combing hair, drinking water, and reaching back, which are the tasks that simulate extremity movements in daily life.
Level of evidence: Basic Science Study; Kinesiology

Keywords: Marker-based motion analysis; markerless motion analysis; 3D motion capture; depth sensors; pose estimation; digital analyses

Accurate analysis of shoulder movements is essential in diagnosis and follow-up of treatment. For this reason, a wide variety of methods is used in the clinic, from a simple goniometer device to a 3-dimensional (3D) marker-based motion analysis system that provides quantitative and objective data.

Computerized 3D marker-based optoelectronic motion analysis systems are considered the gold standard, and they

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are the most accurate method for evaluating a joint range of motion (ROM).[24] In addition, the International Society of Biomechanics (ISB) marker placement and joint coordinate system definitions for the upper extremity make this method more accurate and reproducible.[20] These systems are based on the principle that infrared optoelectronic cameras tract passive reflective markers stuck on specific body points. However, despite the superior precision, the high cost, the need for experienced operators, and extended imaging and analysis processes push researchers to seek less costly, noninvasive, and user-friendly systems. All these requirements have led to the rapid spread of depth sensor–based systems.

The depth sensor provides a depth image of the environment by detecting the pattern reflected on the surface by the infrared dots created by its projector. Furthermore, processing the depth image supplies recognition of the joints between previously defined body segments and determines their coordinates. Thus, body movements can be detected and tracked by the complementary sensor in 3D. Finally, the obtained data are analyzed simultaneously, noninvasively, and efficiently.

The most well-known depth sensor is the Kinect (Microsoft, Redmond, WA, USA). After Kinect v1, which was released in 2010 and attracted much attention in motion analysis, Microsoft released Kinect v2 (Microsoft, Redmond, WA, USA), a more advanced version in 2014. Kinect v2 is used in gait analysis,[2] upper extremity motion,[4,5,26] posture analyses,[22] and ergonomics studies.[11] Analyses can be performed to realize basic joint movements[26] or tasks[4] simulating the movements used in daily life. In addition, they have also used follow-up of a patient with shoulder limitation[12] or in the telerehabilitation.[15] Moreover, it is frequently used in digital game-based applications developed to rehabilitate children.[10] Studies compare the Kinect v2 with a goniometer[5] or 3D marker-based motion systems to test the accuracy of the obtained shoulder ROM.[4] However, none of them has provided sufficient evidence of the device's suitability for clinical use, and therefore, the use of such new devices is still a matter of debate.[1,21]

Although the first 2 generations of Kinect are for game consoles, they have also started to be used in scientific studies after realizing their usefulness in motion analysis. As a result, the last of these sensors, Azure Kinect (Microsoft, Redmond, WA, USA), released in 2019, is no longer produced for game consoles but industrial and scientific purposes. Recent studies testing this new version have reported that Azure is superior to its predecessors in precision (repeatability).[18] Moreover, Azure Kinect has been reported to detect skeletons more smoothly than other versions besides its accuracy and sensitivity.[17] However, although the performance of Azure Kinect has been tested in clinical applications such as gait analysis,[2] scoliosis imaging,[6] and patient pose estimation during surgery,[14] there is no study showing its performance on the shoulder joint.

This study compares the reliability and agreement of Kinect Azure and Kinect v2 with the gold standard marker-based motion analysis system in basic shoulder movements.

Materials and methods

This prospective study included a total of 20 healthy volunteers, ten males and ten females, without any shoulder pathology history. Each volunteer's American Shoulder and Elbow Surgeons score was 100 points. The average age and body mass index (BMI) of the volunteers were 27.9 ± 4.8 years (range, 23-41) and 24 ± 4 (range, 19-32), respectively. All participants were of Caucasian ethnic origin, and all had undergraduate or postgraduate education. Analyses were performed by an experienced physiotherapist (SK). The dominant shoulders of the volunteers were analyzed. Volunteers were asked to perform flexion, abduction, and internal rotation (IR) and external rotation (ER) movements in the shoulder joints while standing. In addition, IR and ER movements were performed when the forearm extended alongside the body and the forearm flexed 90°. The movements were explained to the volunteer in detail by an experienced physiotherapist. Motion capture was performed using Kinect v2 and Azure Kinect depth sensors and BTS SMART DX-100 (BTS Smart DX100, BTS Bioengineering, Milan, Italy) marker-based 3D motion analysis system. After testing the reliability of Kinect and Azure against the gold standard system, we tested the observer-driven performance of the 2 devices. To do this, we performed measurements on ten volunteers that had not been analyzed before. The average age and BMI of the volunteers were 24 ± 5.8 years (range, 18-37) and 22.3 ± 3 (range, 17-28), respectively. All participants were of Caucasian ethnic origin, and all had undergraduate or postgraduate education. Motion capture of these volunteers was recorded and analyzed by 2 different experienced physiotherapist observers (RS and YY). For intraobserver reliability, one observer (RS) performed recording and analysis twice. Ideally, movements should be recorded simultaneously by all 3 systems. However, Kinect Azure cannot function properly due to interference caused by infrared rays created by optoelectronic cameras reflected from passive markers.[16] It is a known issue that causes multipath interference where detected infrared rays will create dark spots on the depth map of the Azure Kinect, regardless of the diameter of the markers used.[25] In summary, pixels are invalidated when they contain a saturated infrared signal. When pixels are saturated, phase information is lost. Therefore, there is no solution other than testing each system separately.

3D marker-based motion capture system and calibration

The marker-based 3D motion analysis system consists of four optoelectronic cameras connected to a computer with a 100-Hz data processing feature. Before the motion capture, the system was dynamically calibrated by moving the calibration bar for ninety seconds in 3 axes to cover the entire motion area. Then, the calibration axis, consisting of 3 vertical calibration bars representing the x-, y-, and z-axis, was placed at a point that four cameras could see, and static calibration was performed for five seconds.

Placement of markers and motion capture

Passive reflective markers (15 mm diameter) were attached to the predetermined anatomical landmarks of all volunteers by the same researcher. The landmarks were as follows: 1) the spinal processes of the seventh cervical, 2) eighth thoracic vertebra, 3) fourth thoracic vertebra, 4) jugular notch, 5) xiphoid process, 6) acromioclavicular joint, 7) sternoclavicular joint, 8) the midpoint of posterior superior iliac spines, 9) the midpoint of the right iliac crest, 10) the midpoint of the left iliac crest, 11) rotation center of the glenohumeral joint, 12) lateral epicondyle, 13) medial epicondyle, 14) acromial angle, 15) trigonum spina, and 16) inferior angle of the scapula. The motions of the shoulder joint were acquired using BTS SMART Capture Software (version 1.10.469.0; BTS Bioengineering, Milan, Italy).

Kinematic model and motion analysis protocol

A model was created from the tracked markers using the BTS Smart Tracker (version 1.10.469.0) software. Next, shoulder joint angular movements were analyzed relative to the thorax by the Euler angle system. Thus, 2 coordinate systems represent the thorax and humerus. For this purpose, a protocol was created using BTS Smart Analyzer software (version 1.10.469.0). First, the kinematic data were interpolated and smoothed; thus, the motion was filtered. Then, x, y, and z vectors were generated from the captured markers to create the humerus and thorax coordinate systems. Next, the coordinate system was created by locating vectors as axes at the origin. Afterward, rotation sequences determined by the shoulder group of the International Society of Biomechanics were used to calculate the angular change between segments.[20] Accordingly, XZY rotation sequences were used for abduction, ZXY for flexion, and XZY rotation sequences for rotations. Finally, the sequence and sequence values of the angular change measured for each movement were determined by marking the maximum and minimum points of the movement (event sequence on one object). The averages of the maximum and minimum values of five sequences were then calculated (cycle sequence mean). Then, the ROM was calculated by determining the difference between the mean maximum and minimum values.

3D motion capture using the depth sensors

Depth sensors were mounted on tripods set at 80 cm height, approximately 150 cm away from the volunteer, to ensure the entire body of individuals and ground were within the field of view and operating ranges of each sensor as suggested by the manufacturers at the maximum point of movement (Fig. 1*A*). Depth sensors were positioned side by side with their axes of vision perpendicular to the frontal plane of the volunteer. The AMD Ryzen 7 3700X 8-Core 3.59 GHz processor desktop (16 GB RAM, NVidia GeForce RTX 2060, version 457.51) computer was used for motion capture and analysis.

For motion capture, the software is required to process the acquired data and create a virtual human skeleton of the recorded subject. In our study, we used the iPiSoft suite (iPi Soft, LLC, Moscow, Russia) consisting of 2 applications: iPi Recorder to capture the motion and iPi Mocap Studio (v 4.5.1.25) to import the recorded data (ie, RGB [red green blue] videos and depth point cloud) and create the virtual skeleton. In addition, the iPi Biomech Add-on module of iPi Mocap Studio, which calculates the kinematic data of the recorded movements, was used. iPi Biomech Add-on is a convenient tool for in-depth biomechanical analysis of human movements. It includes visualizing and converting monitoring data into various formats. This plugin enables gait analysis and rehabilitation research, sports motion analysis, and 3D human kinematics.

Care was taken to ensure that the volunteers did not wear baggy clothing with bright fabrics that would hinder recognizing their body shape. Before the motion capture, the background, a picture of still objects in the field of motion that would be captured, was recorded for five seconds using the "background" feature enabled in the iPi Recorder, and any changes in this area were avoided during motion capture. When recording the background, care was taken not to have a moving object in the camera's field of view and to have as few objects as possible. Following the motion capture, the background was embedded in the captured videos, and thus, the subject's movements were detected. Finally, each shoulder movement was recorded in the iPivideo format on the computer.

Tracking of the Mocap

The recorded videos were processed with the iPi Motion Capture Studio software. First, the gender, height, and BMI values were entered, and the appropriate virtual actor was created for the corresponding volunteer. Once the volunteer's recording and the actor were roughly matched manually at the first frame, the software automatically fits the remaining frames (Fig. 1*B*).

Analyses of tracked Mocap

Biomechanical analysis was performed with the iPi Biomech Add-on. Appropriate Eulers were selected, and the software automatically evaluated the angle values corresponding to seconds during the movement. The data exported to MATLAB (The MathWorks Inc., Natick, MA, USA) and graphs representing each movement were obtained. The maximum and minimum values of the movement were determined on these graphs. The average of the maximum and minimum values of five repetitive movements was calculated. The ROM value was calculated from the differences between the mean.

Statistical analyses

The sample size of the study was calculated as at least 20 volunteers (with 5% dropout) by a sample size calculator[3] based on the following criteria: minimum acceptable reliability (intraclass correlation coefficient [ICC]) (ρ_0) 0.6, expected reliability (ICC) (ρ_1) 0.9, the level of significance (α) at 0.05 2-tailed, and power of the study (1-β) at 90%. Data from previous articles were not used to calculate the sample size.

IBM SPSS Statistics software (version 23; IBM, Armonk, NY, USA) was used for statistical analysis. Two separate observers repeated the measurements with both sensors to test the measurements' reproducibility. The reliability between the methods was evaluated using the ICC (3, k), and the reliability between the

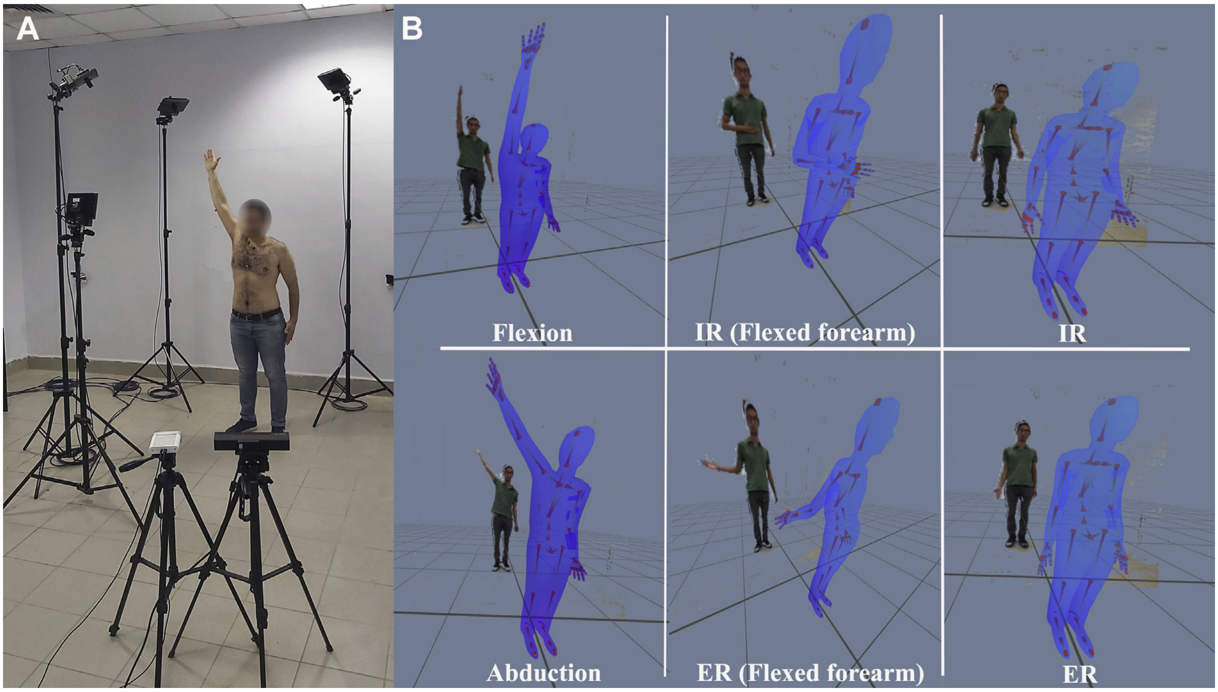

Figure 1 Use of 3 different 3D motion analysis systems to measure the shoulder ROM. (**A**) Positioning of all 3 systems and the individual's position in front of the cameras. (**B**) Adapt captured movements using depth sensors to the virtual actor with iPi soft software. *3D*, 3-dimensional; *ROM*, range of motion; *ER*, external rotation; *IR*, internal rotation.

observers was evaluated by the ICC (3, 1). In addition, Bland-Altman analyses were used to evaluate the agreement between the methods.

ICC evaluation values between 0.20 and 0.60 were accepted as poor agreement, between 0.6 and 0.9 as high agreement, and above 0.9 as excellent agreement. The limits of agreement (LOAs) were expected to include 95% of the difference between measurement systems and were defined as mean $\pm$ 1.96 $\times$ standard deviations.

The errors between the systems were determined by calculating the standard error of the mean (SEM) and minimal detectable change (MDC). The SEM was calculated with the use of the ICC. It was calculated with the following formula: SEM= standard deviation x [square root of (1-ICC value)]. The following formula calculated the MDC for the 95 % confidence interval: MDC = SEM x 1.96 x square root of 2.[19]

Results

We tested the intraobserver and interobserver reliability of the measurements from both sensors in a test-retest situation. We determined that the reproducibility varies depending on the movement performed. The intraobserver and interobserver reliability of the Kinect sensor was from 0.47 to 0.84 and 0.64 to 0.96, respectively. The intraobserver and interobserver reliability of the Azure sensor was from 0.64 to 0.91 and 0.60 to 0.97, respectively (Table I).

When the reliability of both sensors according to the BTS system was examined, similar ICC values were detected in flexion (0.86 vs. 0.82), abduction (0.78 vs. 0.79), IR (flexed forearm, 0.74 vs. 0.70), and ER (flexed forearm, 0.60 vs. 0.66) movements. On the other hand, ICC values of IR (0.49 vs. 0.75) and ER (0.38 vs. 0.67) movements were higher for the Azure sensor. Furthermore, the determined MDC and SEM values of Azure were lower for IR (4 vs. 7 for SEM, 10 vs. 19 for MDC) and ER (5 vs 8 for SEM, 13 vs 22 for MDC) than those of Kinect (Table II).

The measurement agreement obtained from both sensors was tested with the Bland-Altman method. The drawn Bland-Altman plots are shown in Figure 2. The mean difference of the measurement (bias) values and 95% confidence interval (LOA) were depicted in Figure 2 and Table II. According to our results, data from both sensors were randomly distributed around zero, and most measurements were in the LOA intervals. The LOA was also similar for both sensors.

While there were significant differences between the abduction (142° vs. 155°) and IR (31° vs. 13°) angle values in comparing the BTS and the Kinect sensor, a difference was observed in the IR (31° vs. 13°) movement compared to the BTS and the Azure sensor. Therefore, while both sensors underestimated the IR ROM, the Kinect sensor overestimated the abduction range (Table III).

Discussion

This study tested the concurrent reliability of basic upper limb movement using Kinect v2 and its successor Azure

Table I Interobserver and intraobserver reliability of Kinect and Azure

n = 10	Kinect				Azure			
	Interobserver		Intraobserver		Interobserver		Intraobserver	
	ICC	95% CI (lower-upper)	ICC	95% CI (lower-upper)	ICC	95% CI (lower-upper)	ICC	95% CI (lower-upper)
Flexion	0.84	0.37-0.96	0.90	0.61-0.98	0.64	−0.47 to 0.91	0.82	0.27-0.96
Abduction	0.78	0.11-0.95	0.64	−0.46 to 0.91	0.93	0.7-0.98	0.58	−0.71 to 0.90
IR (flexed forearm)	0.65	−0.42 to 0.91	0.96	0.84-0.99	0.89	0.56-0.97	0.97	0.89-0.99
ER (flexed forearm)	0.56	−0.77 to 0.89	0.73	−0.11 to 0.93	0.79	0.15-0.97	0.81	0.23-0.95
IR	0.52	−0.93 to 0.88	0.88	0.50-0.97	0.70	−0.21 to 0.93	0.79	0.14-0.95
ER	0.47	−1.13 to 0.87	0.85	0.39-0.96	0.82	0.26-0.96	0.94	0.77-0.99

ICC, intraclass correlation coefficient; *CI*, confidence interval; *IR*, internal rotation; *ER*, external rotation.

Table II The reliability and agreement between the methods

n = 20	Kinect/BTS					Azure/BTS					Kinect/Azure				
	Bias	LOA	ICC	SEM	MDC	Bias	LOA	ICC	SEM	MDC	Bias	LOA	ICC	SEM	MDC
Flexion	−2.6	−17.2 to 11.9	0.86	3	8	−4.0	−20.2 to 12.3	0.82	4	10	−1.3	−12.1 to 9.5	0.92	2	4
Abduction	−12.5	−36.9 to 11.8	0.78	6	16	−9.6	−31.9 to 12.7	0.79	5	14	2.9	−5.9 to 11.7	0.98	1	2
IR (flexed forearm)	6.0	−15.3 to 27.3	0.74	6	15	4.6	−19.1 to 28.2	0.70	7	18	−1.5	−11.7 to 8.8	0.96	1	3
ER (flexed forearm)	−6.0	−29.9 to 17.9	0.60	8	21	−7.3	−31.0 to 16.4	0.66	7	20	−1.3	−16.3 to 13.7	0.92	2	6
IR	17.4	−1.7 to 36.5	0.49	7	19	17.7	3.4 to 32.1	0.75	4	10	0.3	−9.0 to 9.6	0.84	2	5
ER	4.0	−16.2 to 24.1	0.38	8	22	3.6	−12.2 to 19.4	0.67	5	13	−0.3	−11.5 to 10.8	0.77	3	8

BTS, marker-based optoelectronic motion capture system; *LOA*, limit of agreement; *ICC*, intraclass correlation coefficient; *SEM*, standard error of the mean; *MDC*, minimal detectable change; *IR*, internal rotation; *ER*, external rotation.

Kinect depth sensors. According to our findings, both sensors showed similar reliabilities in flexion and abduction movements, while Azure Kinect performed better in rotation. Our study is the first on this subject to the best of our knowledge.

Contrary to depth sensors, marker-based systems cause a loss of time during marker placement, and markers negatively affect patient comfort. In addition, unwanted reflections can cause phantom marker registration. On the other hand, the lower cost of the depth sensor–based system allows patients to use them at home, thus enabling telerehabilitation and follow-up. The problem to be solved for these systems is accuracy.[7] In addition, when a single camera is used, the shadowing of the joints by the body parts is a significant problem. The shadowing problem can be overcome with multiple cameras, but this requires camera synchronization and increases costs.

This study determined that Azure Kinect and Kinectv2 have similar high-reliability values in predicting movements with a high ROM, such as flexion and extension. A similar relationship has also been reported in a previous study testing reliability of the Kinectv2 with a marker-based system, stating that the error size was proportional to the size of that joint angle.[23] Accordingly, the error size of the Kinect v2 was smaller in movements with a broader ROM value such as flexion, while it was higher in the movements with a relatively lower ROM value such as rotation movement. Furthermore, in a study investigating the reliability of the Kinect v2 in assessing functional shoulder tasks, the results were compared with the gold standard marker-based motion analysis system.[4] Accordingly, it was reported that the Kinect v2 showed high and moderate accuracy in the evaluation of flexion/extension and abduction/adduction movements, respectively, while it showed low accuracy in IR and ER.

Another important finding of this study is that Kinect Azure showed higher reliability than Kinectv2 in estimating the movements with low ROM values such as IR and ER. Namely, both sensors showed lower reliability during shoulder rotation with the extended forearm alongside the body, while the Kinect Azure performed better with the flexed forearm. Prediction success due to joint position can be explained by the nature of the machine learning algorithm underlying the 3D human pose

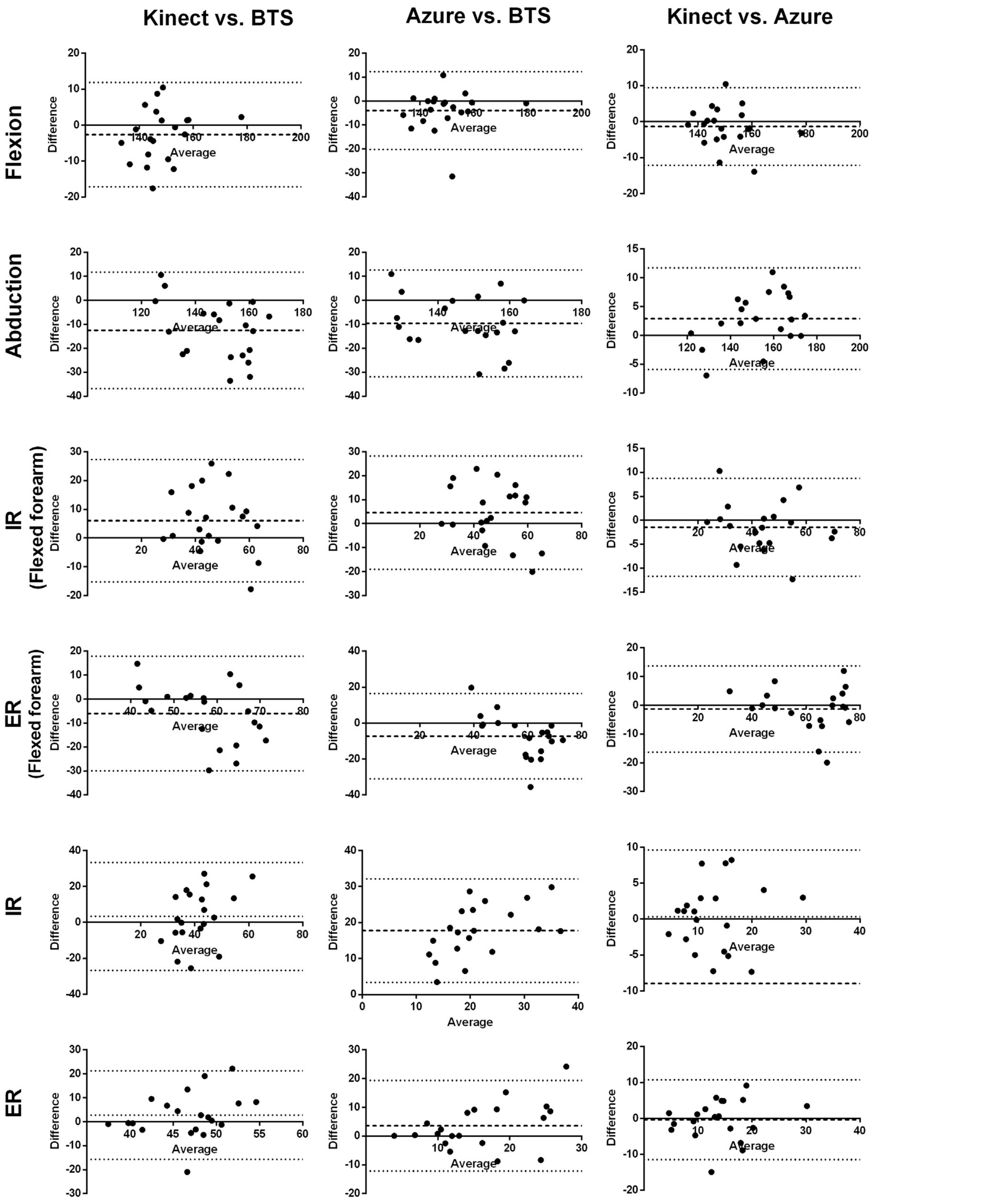

Figure 2 Graphical representation of agreement between the methods by the Bland-Altman plots. The dashed line in the *middle* indicates the mean differences, and the *upper* and *lower* dashed lines show 95% limits of agreement (mean differences ± 1.96 standard deviations of the difference). *ER*, external rotation; *IR*, internal rotation; *BTS*, marker-based optoelectronic motion capture system.

Table III The comparison of angular pose estimation of the shoulder joint obtained by 3D three systems

n = 20		Mean	Std. deviation	P value		
				Kinect/BTS	Azure/BTS	Kinect/Azure
Flexion	BTS	147	11	>.9999	.6249	>.9999
	Kinect	150	9			
	Azure	151	10			
Abduction	BTS	142	12	**.0267**	.1104	.8118
	Kinect	155	17			
	Azure	152	15			
IR (flexed forearm)	BTS	49	11	.2917	.4897	.9282
	Kinect	43	13			
	Azure	45	14			
ER (flexed forearm)	BTS	55	8	.2889	.1657	.9452
	Kinect	61	14			
	Azure	62	15			
IR	BTS	30	10	**<.0001**	**<.0001**	>.9999
	Kinect	13	7			
	Azure	13	6			
ER	BTS	18	9	.2444	.3071	.9891
	Kinect	14	7			
	Azure	14	6			

BTS, marker-based optoelectronic motion capture system; *IR*, internal rotation; *ER*, external rotation.
P values less than .05 were considered statistically significant.

estimation performed via a single 3D depth sensor and 2-dimensional camera.[13] Since a global optimization algorithm using posture in an environment achieves the final position prediction, the joint shadowed by any body part will cause difficulty in identifying the point corresponding to this joint in the skeletal model of the Kinect system. In our example, it may be easier to distinguish the arm rotation with flexed arm, preventing such shadowing and leading to more accurate pose estimation. Thus, when considering the relationship between reliability and measurement error,[8] Azure Kinect's high reliability can be attributed to its lower measurement error.

Azure Kinect is more accurate and precise than its discontinued predecessors,[17] has lower depth noise,[18] and has more accurate calibration for intrinsic parameters allowing more accurately converting depth maps to 3D points.[16] Intrinsic parameters include the camera's lens distortions, mutual positions, and rotations for RGB, IR, and depth cameras. The more accurate intrinsic calibration is, the more accurate the 3D point cloud corresponds to the actual body surface. Tracking accuracy depends on many factors, and the most important factors are the tracking algorithms used, input data, and setup. In addition, the algorithm finds the best match between the built-in human actor model and the 3D point cloud, which leads to better results when we get better input data. The hardware superiority of Azure Kinect may have contributed to the accurate position estimation we have mentioned above.

The significant limitation of our study is the known interference of Kinect Azure with infrared rays reflected from passive markers, which was reported by the manufacturer[16] and in the previous study.[25] Although this prevents us from testing the 3 systems synchronously, we believe operating both depth sensors concurrently is sufficient to test our hypothesis. In addition, assessing the patients with shoulder limitations could also provide information about the success of the systems in revealing the differences with the healthy group and in the follow-up of changes in the ROM over time. Nonetheless, healthy individuals' upper limb motions often have lower variability in contrast to the patients. The lower variability decreases heterogeneity, leading to lower reliability estimates and weak correlations between the sensor and gold standard method. Therefore, cohorts of healthy individuals have higher discrimination in testing the distinguishability of measurement devices and measurement error.[8,9]

Conclusion

Azure Kinect can perform better position estimation, thanks to its superior hardware, than its previous generation predecessor could. In the analysis of kinematic data, besides the hardware, the software used is also critical. Apart from the software we use in our study, we think it is important to test other software solutions created by the customer or purchased commercially in the market. In addition, comprehensive studies to be carried out in large cohorts, including patients, will provide an opportunity to gain better insight into new-generation markerless motion capture technologies.

Disclaimers:

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