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'DIGITS' app - smartphone augmented reality for hand telerehabilitation

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ABSTRACT

Hand telerehabilitation currently has limitations for accurate and remote assessment of range of motion (ROM) in small finger joints. 'DIGITS' application utilises the front smartphone camera to measure finger ROM in a reliable and rapid assessment protocol. Our initial beta-phase testing examined the consistency of our software measurements to in-person goniometry. 6 to 9 degrees of difference existed between the smartphone application recorded data versus the in-person measurements. This range is within acceptable 7 to 9 degree tolerance for interrater goniometry measurements. The effect of environmental factors such as hand distance, lightings and hand orientation was evaluated. The intraclass correlation coefficient (ICC) was 0.98–0.98 for finger extension and 0.78–0.81 for finger flexion recorded across different environmental conditions. Overall, 'DIGITS' provides an augmented reality tool to generate reliable finger ROM tracking for hand telerehabilitation. 'DIGITS' has the potential to transform hand therapy and improve our knowledge of hand pathology recovery.

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Telerehabilitation; computer vision; range of motion

Introduction

Telerehabilitation and remote patient monitoring have expanded significantly in recent years, even prior to the recent widespread adoption secondary to the COVID-19 pandemic (Field and Grigsby 2002; Logan et al. 2007; Vegesna et al. 2016; Malasinghe et al. 2019). Augmented reality (AR) provides interactive experience to users by superimposing virtual information on the real world (Silva et al. 2003; Cipresso et al. 2018; Chen et al. 2019; Flavián et al. 2019; Berton et al. 2020). Integration of AR in imaging, surgical planning and therapy is directly beneficial to patient care (Eckert et al. 2019; Yeung et al. 2021). New applications of AR systems in healthcare evolving, and some of the previous generation AR solutions are limited by their upfront cost and accessibility (Zhao et al. 2016; Ara et al. 2021). However, with increasing affordability of the AR systems, the adoption of such technology will significantly reduce the overall cost to the system and to the patients (Kulkov et al. 2021). In addition, secondary benefits of AR in telerehabilitation include more robust standardised data collection opportunities to reflect the patient's rehabilitation journey.

Bimanual hand function is important for activities of daily living but also for the majority of vocations. Hand trauma, surgery, or arthritis can result in significant disability. Regaining the full range of motion of the digits and avoiding stiffness is of paramount importance. Rehabilitation with a certified hand therapist is an integral component of patient care (Meals and Meals 2013; Hartley et al. 2020). Consistent assessment and hand therapy are linked to improved functional outcomes in terms of recovery of strength and range of motion (Duncan et al. 1993; Hays and Rozental 2013; Hepping et al. 2020) following hand injuries.

Given the increasing need for accessible solutions for the assessment of patients with hand injuries, there is an opportunity to address this problem with modern AR technology. It is our focus to introduce a low-cost and high-accessibility framework that will be easily adopted within current clinical workflows. In the present work, we aimed to develop an easily accessible remote assessment tool for the finger range of motion assessment. We designed an AR application ('DIGITS') that utilises the front facing camera of a smartphone to track bony landmarks of the hand using deep learning. It is currently developed for the Android platform, and in development for iOS. Using the 2.5D coordinates of the landmarks tracked through machine learning, angles and the range of motion between the small joints of the hand were recorded in real time. The application is written in Java and C++ programming languages and is adapted from the open source MediaPipe Hands pipeline (Zhang et al. 2021).

In the current study, we aim to validate our system as a stable, reliable, efficient, and accurate method of remote assessment tool for finger joint range of motion of healthy hands. We established a preferred external environment for assessment and performed real-time on-device measurements of our range of motion in the small joints of the hand for flexion and extension arcs of digits 2–5 (index, middle, ring and small) [Figure 1(a)]. These measurements were compared to the in-person measurements obtained by a certified hand therapist.

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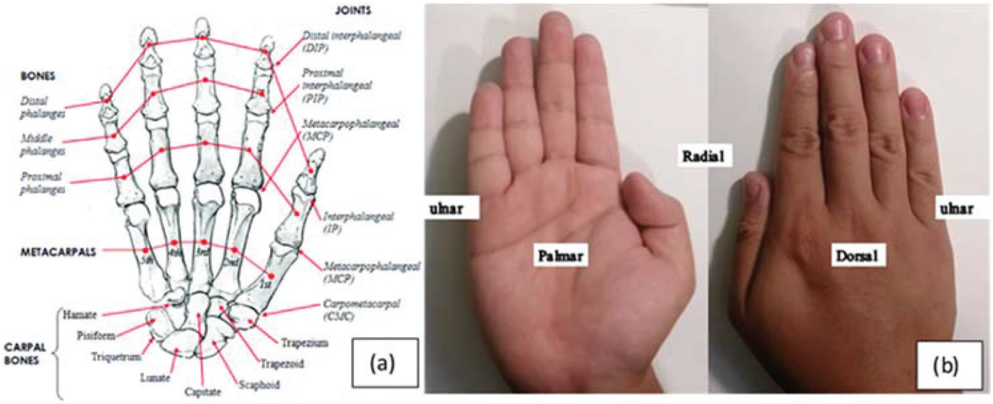

Figure 1. (a) Bone anatomy of the hand (Nanayakkara et al. 2017). (b) Palmar, Dorsal, Ulnar and Radial surfaces of the hand as noted.

Additionally, the reproducibility of these results was studied by repeating the measurements in different light settings as well as hand object distances and orientations from the camera.

A few current studies explored telerehabilitation through adaptive gaming systems, hand-finger motion tracking, virtual reality, and the use of remote-controlled exoskeleton (Lockery et al. 2011; Pham et al. 2015; Berton et al. 2020; Kim et al. 2020). However, most require costly robotics and equipment that are only accessible in treatment centres. There is one study that assesses finger range of motion utilising a smartphone as an alternative goniometer to individually measure each joint individually, which, while comparable to standard finger goniometry, is distinct from our project since our system assesses all the joints simultaneously in a much shorter time frame (Miyake et al. 2020). One notable difference between the two is that the measurement time is 2 minutes (which is better when compared to in-person goniometer which is greater than 4 minutes) to complete the assessment of the joints of one hand, we are able to capture angle data of a whole hand 15 times per second, which is arguably more convenient for patient use when it is integrated to a part of a telerehabilitation programme. There are no currently available studies utilises accessible smart phone applications as a way of conducting both rapid remote assessment and telerehabilitation of finger ROM.

Future work will include the analysis of pathological and traumatic hands across different patient populations. Artificial intelligence and machine learning will be implemented to improve our tracking power as well pattern recognition of the pathology as well as prognostic data analysis. The overarching goal is to develop a low-cost, accessible and accurate assessment tool of finger range of motion for the clinical application of telerehabilitation of patients with hand pathologies.

Materials and methods

Joint range of motion assessment with goniometer

The range of motion (ROM) for flexion and extension was assessed by a certified hand therapist with a goniometer on three separate occasions in the 0–180 system, where the distal end of a joint was moved from the starting neutral position to the end position of the motion (Schiefer et al. 2015). Assessment included the following phalanges: index, middle, ring and small. We measured the metacarpophalangeal (MCP), proximal interphalangeal (PIP), and distal interphalangeal (DIP) joints in the right hand of a right-hand dominant male [Figure 1(a)]. The goniometer was placed on the top of the dorsal surface, along the radial side, or along the ulnar side of the hand depending on where a visual evaluation and estimation of the location and angle between the bones could be made. The anatomical nomenclature of the surfaces of the hand (dorsal, palmar, ulnar and radial) is shown in Figure 1(b).

The absolute mean of the resulting three sets of measurements was used to assess the agreement with the 'DIGITS' application joint ROM assessment. It is noted that the standard intra-rater goniometry margin of error falls within 4–5 degrees, whereas the inter-rater goniometry falls within 7–9 degrees (Ellis and Bruton 2002).

Joint range of motion assessment with DIGITS – the android application

Systems and data collection

The hand range of motion data was collected using DIGITS, a custom Android software application utilising the MediaPipe Hands pipeline (Zhang et al. 2021). In short, this pipeline utilises two convolutional networks: the first is a modified single-shot detector (Liu et al. 2016) model, which detects the location of palms in an image, and the second is a regression model, which detects the 2.5-dimensional landmarks within the hand (x, y, and relative depth coordinates). These networks were implemented and trained by the MediaPipe authors in Tensorflow (Abadi et al. 2016).

The landmark coordinates and timestamp were logged in real time into a comma separated values (CSV) text file on the mobile device. The vectors between each of the hand landmarks are used to calculate the angle between each finger and hand segment, yielding the corresponding joint angle. Given two adjacent segments x_1 and x_1, the angle θ was simply calculated as

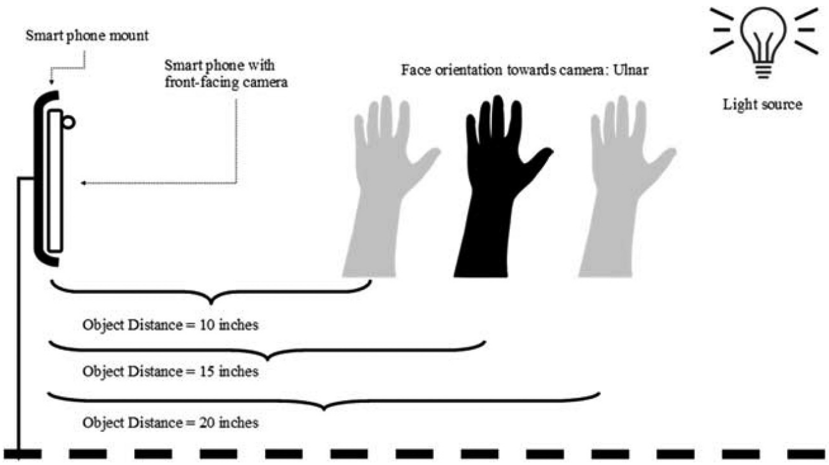

Figure 2. This demonstrates our data collection experiment setup. Minimal equipment is required: a smart phone, 'DIGITS' application and an adjustable light source.

$$\theta = \arccos\left(\frac{\overrightarrow{x_1}.\overrightarrow{x_2}}{\left|\overrightarrow{x_1}\right|\left|\overrightarrow{x_2}\right|}\right)$$

Setup for ROM measurement

The Android device (Huawei P30Lite, with high-res 24MP front-facing camera behind f/2.0 lens) was fixed to a flat surface and is angled 90 degrees perpendicular to the ground. The right hand of the test subject was placed around 10,15 and 20 inches away from the screen to allow for full visibility by the camera (Figure 2). Assessment included the following fingers: index, middle, ring and small. We measured the MCPs, PIPs, DIPs in the right hand of a right-hand dominant male. The test subject was instructed to either hold a full fist (flexion) or to lay the palm flat (extension).

The landmarks of each finger joint of the hand were identified and tracked by our system in real-time, and the angles between adjacent segments were calculated to estimate the range of motion end points across the different joints of the hand.

The data set has a sampling frequency of 15 per second, and the mean sampling time for each data set is 30 seconds. This resulted in an average of 450 data entries of whole-hand ROM measurements per data set. We experimentally controlled face orientation towards the camera (ulnar, palmar or rotational from ulnar to palmar as demonstrated in Figure 3) object distance (10, 15 or 20 inches) or light setting (bright, normal, dim or dark as defined in Figure 4) and collected 3 identical repeats of data sets at each distinct environmental setting. In total, we had 54 individual data sets collected for flexion, and another 54 sets for extension for the right hand and 9 sets were collected for flexion and extension for the left hand.

Data processing procedures

The data output is recorded in the *.CSV*, which was then used to calculate the 3D vector angle. Each data set's samples were averaged. The standard deviation was calculated based on the intra-dataset mean. Accuracy was assessed through mean absolute error in degrees and percent error.

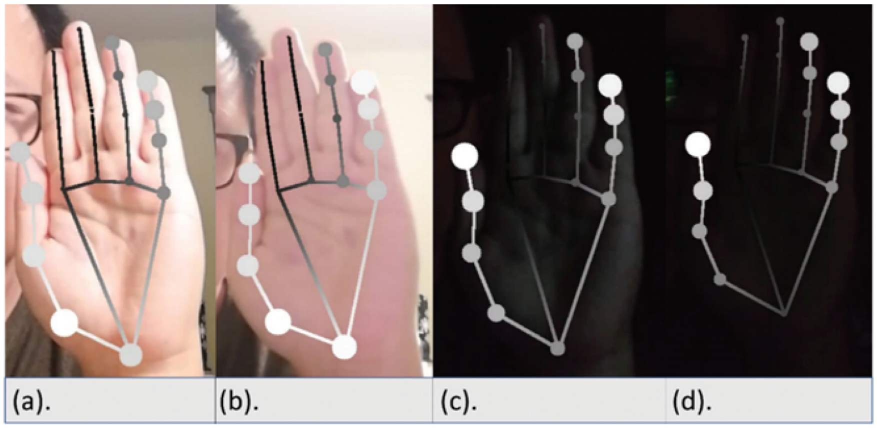

Figure 3. This illustrated the different hand positions from which the data was collected: (a) flexion and palmar facing (b) flexion and ulnar facing (c) extension and ulnar facing and (d) extension and palmar facing.

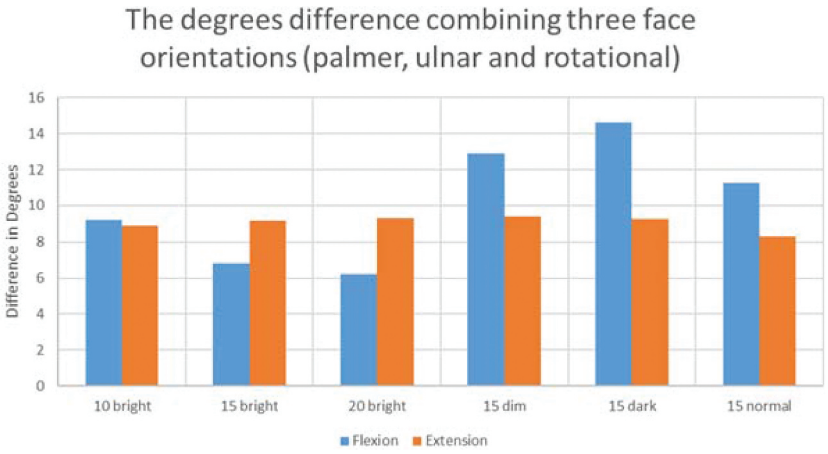

Figure 4. This illustrated the different light conditions from which the data was collected: (a) bright (b) normal (c) dim and (d) dark.

ANOVA analysis and Intraclass Correlation Coefficients (ICCs) were calculated in both flexion and extension data sets separately.

Results

There are 450 total samples per dataset, with a sampling time of 30 seconds each and a sampling frequency of 15 Hz. Datasets collected in the fixed face orientation (ulnar or palmer) towards the camera had a higher precision as measured by intra-dataset standard deviation (3.1 SD) than the data sets collected which hand in constant rotation (9.1 SD). Additionally, when we look at all 126 sets of data (56,700 samples), there is a 7.0 SD across all 63 datasets for flexion and a 3.2 SD for all 63 datasets for extension, showing a higher precision when measuring extension as seen in Table 1. Similar results are collected for the left hand in Table 2.

When combining three face orientations (ulnar, palmar, hand in constant rotation), the flexion dataset's difference to absolute true value (goniometry data) is less consistent (right hand 6.19 to 14.60 degrees, left hand 7.09) across datasets than extension (right hand 8.31 to 9.38 degrees, left hand 5.36) as reported in Figure 5 and supplemented by Table 2. This is once again reflected by their respective ICC across the 126 datasets each: flexion (0.81 R, 0.78 L) and extension (0.98 R, 0.98 L) in Table 3.

Measurements by certified hand therapists of the flexion and extension angles are recorded in Table 4.

The joint angle of the same hand position varies between face orientations, and best accuracy is reported when all three orientations are combined. Accuracy is measured in terms of its deviation from the average of the in-person measurements. In flexion, we obtained the most accurate dataset with only 6.19 degrees difference at 20 inches object distance and 'bright' light setting. In extension, it was consistently around 9.05 degrees of difference with all object distance and lighting.

Lighting not only affects the precision in a less illuminated environment, and it also appears to impact the data collection process itself by lowering the number of times the application can register data. The landmarks were not able to be recognised during the entirety of the data collection time, resulting in the dataset collected under the dark setting having recorded far less data entry than in all other light settings.

Table 1. The degree differences are as compared to goniometer measurement as noted in Table 4 for the right hand and the standard deviation is based on the intra-dataset samples. Object differences are as recorded (10″, 15″ and 20″), light settings are as noted (bright, normal, dim and dark), and the direction of the hand facing the phone camera is (ulnar, palmar or rotational, which is defined as the hand in constant rotation between ulnar and palmar).

	Degrees difference	SD
Flexion-10″-bright-palmar	24.63	3.91
Flexion-10″-bright-rotational	13.24	12.75
Flexion-10″-bright-ulnar	13.31	2.75
Flexion-15″-bright-palmar	20.23	3.37
Flexion-15″-bright-rotational	12.36	12.43
Flexion-15″-bright-ulnar	12.81	5.15
Flexion-20″-bright-palmar	16.82	7.60
Flexion-20″-bright-rotational	15.59	11.50
Flexion-20″-bright-ulnar	13.61	4.85
Flexion-15″-normal-palmar	24.26	2.50
Flexion-15″-normal-rotational	17.64	10.77
Flexion-15″-normal-ulnar	14.44	4.79
Flexion-15″-dim-palmar	30.16	2.36
Flexion-15″-dim-rotational	17.67	10.71
Flexion-15″-dim-ulnar	15.81	4.99
Flexion-15″-dark-palmar	27.47	3.21
Flexion-15″-dark-rotational	26.25	16.21
Flexion-15″-dark-ulnar	21.55	5.52
Extension-10″-bright-palmar	9.40	1.81
Extension-10″-bright-rotational	12.79	5.69
Extension-10″-bright-ulnar	12.58	2.19
Extension-15″-bright-palmar	9.80	1.42
Extension-15″-bright-rotational	12.44	6.26
Extension-15″-bright-ulnar	13.31	2.08
Extension-20″-bright-palmar	10.48	1.78
Extension-20″-bright-rotational	11.99	5.36
Extension-20″-bright-ulnar	12.34	1.81
Extension-15″-normal-palmar	8.92	1.89
Extension-15″-normal-rotational	12.63	6.31
Extension-15″-normal-ulnar	11.88	1.67
Extension-15″-dim-palmar	10.49	1.82
Extension-15″-dim-rotational	12.40	6.13
Extension-15″-dim-ulnar	13.33	2.90
Extension-15″-dark-palmar	10.47	1.75
Extension-15″-dark-rotational	10.83	4.74
Extension-15″-dark-ulnar	12.98	2.34

Table 2. The degree difference is as compared to goniometer measurement as noted in table 2 for the left hand, and the standard deviation is based on the intra-dataset samples. Object differences are as recorded at 20″ inches, light setting is bright, and the direction of the hand facing the phone camera is ulnar, palmar or rotational, which is defined as the hand in constant rotation between ulnar and palmar.

	Degrees difference	SD
Flexion-20″-bright-palmar	27.65	2.13
Flexion-20″-bright-rotational	9.68	13.00
Flexion-20″-bright-ulnar	14.32	2.90
Flexion-20″-bright-combined view	7.09	
Extension-20″-bright-palmar	7.78	1.52
Extension-20″-bright-rotational	6.87	4.79
Extension-20″-bright-ulnar	7.98	1.47
Extension-20″-bright-combined	5.36	

The data when accounted for object distance appear to be relatively comparable when the whole hand is visible in the camera at distances of 10 inches, 15 inches and 20 inches. For standardisation of procedure, we determined 15–20 inches object distance in the bright illumination to be the section with desirable accuracy and precision.

Discussion

'DIGITS' provides precision and reliability for remote monitoring of finger range of motion, with the ability to assess the end point range of motion. In the literature, the goniometer assessment by a certified hand therapist has an accepted intra- versus

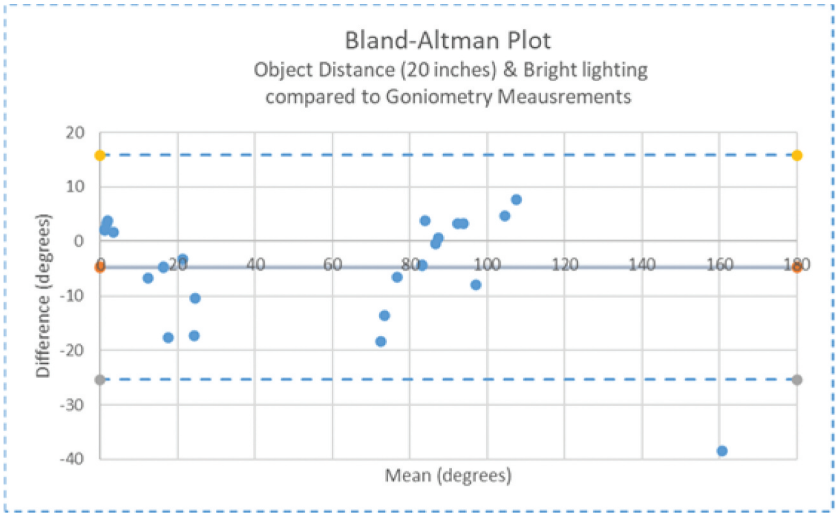

Figure 5. The degrees difference (comparing goniometry and 'DIGITS' application) of the right hand when combining three face orientations (palmer, ulnar and rotational motion view) under different object distance (10, 15, 20 inches) and light setting (bright dim dark normal).

Table 3. ANOVA analysis and intraclass correlation coefficients (ICC) were analysed for both left hand and right hand datasets.

ANOVA – Flexion		Right				
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Rows	627,411.2	14	44,815.08	233.6193	1.3E-260	1.705114
Columns	10,467.28	53	197.4958	1.029538	0.419443	1.357424
Error	142,337.5	742	191.8296			
Total	780,216	809				
	ICC	0.811296				
ANOVA – Extension		Right				
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Rows	844,786.1	14	60,341.86	5555.498	0	1.705114
Columns	1003.618	53	18.93619	1.743399	0.00113	1.357424
Error	8059.343	742	10.86165			
Total	853,849.1	809				
	ICC	0.979892				
ANOVA – Flexion		Left				
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Rows	92,275.16	14	6591.083	32.81506	3.97E-33	1.78105
Columns	1191.851	8	148.9813	0.741734	0.654501	2.022093
Error	22,495.81	112	200.8554			
Total	115,962.8	134				
	ICC	0.782464				
ANOVA – Extension		Left				
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Rows	143,499.2	14	10,249.95	382.1126	1.59E-87	1.78105
Columns	301.6779	8	37.70974	1.4058	0.201722	2.022093
Error	3004.334	112	26.82441			
Total	146,805.2	134				
	ICC	0.97632				

Table 4. The in-person goniometry measurement of both hand fingers' range of motion used as a true value in analysing the data obtained from DIGITS app's precision and accuracy.

	Index MCP	Index PIP	Index DIP	Middle MCP	Middle PIP	Middle DIP	Ring MCP	Ring PIP	Ring DIP	Small MCP	Small PIP	Small DIP
Right Flexion	87.00	101.00	81.67	89.33	102.33	82.00	87.67	103.67	80.00	94.67	93.00	80.33
Right Extension	23.00	26.33	0.00	0.00	33.00	0.00	0.00	29.67	0.00	18.67	15.67	2.67
Left Flexion	86.00	100.00	84.00	80.00	101.00	87.00	85.00	105.00	71.00	90.00	90.00	81.00
Left Extension	8.00	6.00	5.00	14.00	15.00	5.00	13.00	14.00	0.00	18.00	1.00	20.00

intertherapist measurement is 5 and 7–9 degrees, respectively (Ellis and Bruton 2002). Our recordings are also within this acceptable range. Our next steps are to create a platform for patients to have access to remote monitoring of hand range of motion recovery.

With intra-application comparison on the palmar face orientation, we maintained 3.8 SD for flexion, and a 1.8 SD for extension of the right hand, whereas a 2.13 SD and 1.52 SD for the flexion and extension of the left hand, respectively. Furthermore, combining three face orientation, we are able to achieve only 5.36–9.38 degree difference under preferred lighting and distance setup when compared to a set of in-person measurements. It is worth noting that both the goniometer measurements and our application are not the 'absolute' true value as it is also an estimation of the joint angle from the skin level. Additionally, we were able to get three separate sets of measurements from a certified hand therapist in person, whereas our dataset has over 56,700 data entries in total at a sampling frequency of 15 Hz. It provides a much more robust and rapid assessment that can be conducted remotely in a time where telehealth is not only sought after but also necessary on some occasions. The ANOVA and ICC analysis has provided excellent reliability of our results for extension (0.98 R, 0.98 L) and good reliability for flexion (0.81 R, 0.78 L) according to the standards reported in the literature (Koo and Li 2016).

We determined that placing the ulnar or palmar surface of the hand towards the front facing camera of the phone, while keeping it still, will provide better precision as shown by our standard deviation.

Additionally, we were also able to determine the optimal lighting (bright) and object distance (15–20) for assessment that can provide the best accuracy and consistency. A Bland-Altman plot was included for distance 20 and lighting bright (Figure 6).

It is also worth noting that while our experiment was conducted using a stand that fixed the phone as shown in Figure 2 for control, it is not a necessary requirement as the application works whenever a hand in full view of the camera.

Our 'DIGITS' application will ultimately offer a more comprehensive platform. After validating the range of motion assessment in patient populations, we plan to further build on the robust potential of our application in velocity and dynamic tracking, as well as our understanding of remote strength and dexterity assessment. In addition, additional remote monitoring capabilities such as scheduling, post-operative monitoring of swelling and potential infection, and self-reported pain scales will ultimately be integrated. All of these aspects will provide us a more comprehensive picture of the recovery of hand function. In collaboration with our local experts in AI, we hope to incorporate machine learning to understand the recovery trajectory of patients with a variety of pathologies, basic demographics, and rehabilitation information. Ultimate expansion can include additional orthopaedic issues including lower extremity.

The next steps involved in this project include examining the baseline range of motion from a healthy population based on demographics such as age and biological sex. Similar measurements can be taken on patients with hand pathologies such as trauma, arthritis, or congenital anomalies. The implementation of this intervention can be studied in a clinical setting in terms of its effect on the speed of post-trauma recovery of the full range of motion. Additionally, the patient satisfaction as well as perceived autonomy with regard to one's own health can be assessed.

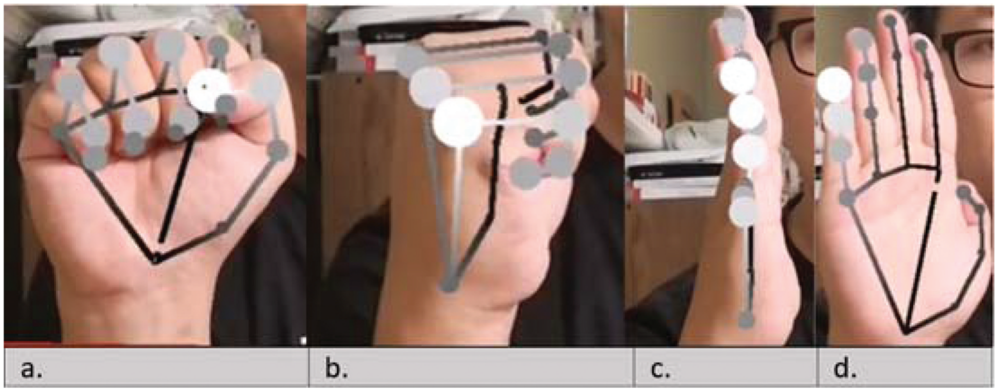

Figure 6. Bland–Altman plot of measurements obtained using the DIGITS application versus the goniometry at 20 inches object distance and light setting (bright) of the right hand. Data used were the range of motion at each finger joints of digit 2–5, and the average of 450 data entries.

With the increasing adoption of telemedicine and virtual care, strong support exists to incorporate AR in the delivery of high calibre care. The 'DIGITS' application will serve as one of the first next generation AR virtual medical care technology for hand telerehabilitation to serve our community's ever-evolving needs.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Dr. Geoffrey Masschelein is a Plastic and Reconstructive surgery resident at Western University with an interest in hand surgery. He completed his medical school, as well as a double major in biology and medical sciences at Western University. His research interests include improving patient outcomes following upper extremity trauma/surgery.

Jacob Davidson completed both his Bachelor of Arts and Master of Science degree in Kinesiology and Physical Education from Wilfrid Laurier University. Jacob started with the Division of Paediatric Surgery in 2017. Currently, he is the Research Coordinator for the Division of Paediatric Surgery and has helped to facilitate a number of clinical, educational, and quality improvement projects in many different surgical sub-specialities.

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References

Abadi M, Barham P, Chen J, Chen Z, Davis A, Dean J, Devin M, Ghemawat S, Irving G, Isard M. 2016. TensorFlow: a system for large-scale machine learning. In: 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16); Savannah, GA, USA; p. 265–283. [Accessed 2021 Jul 2]. https://www.usenix.org/system/files/conference/osdi16/osdi16-abadi.pdf

Ara J, Karim FB, Alsubaie MSA, Bhuiyan YA, Bhuiyan MI, Bhyan SB, Bhuiyan H. 2021. Comprehensive analysis of augmented reality technology in modern healthcare system. Int J Adv Comput Sci Appl (IJACSA). 12:6. doi:10.14569/IJACSA.2021.0120698.

Berton A, Longo UG, Candela V, Fioravanti S, Giannone L, Arcangeli V, Alciati V, Berton C, Facchinetti G, Marchetti A, et al. 2020. Virtual reality, augmented reality, gamification, and telerehabilitation: psychological impact on orthopedic patients' rehabilitation. J Clin Med. 9(8):2567. doi:10.3390/jcm9082567.

Chen Y, Wang Q, Chen H, Song X, Tang H, Tian M. 2019. An overview of augmented reality technology. J Phys. 1237:022082. doi:10.1088/1742-6596/1237/2/022082.

Cipresso P, Giglioli IAC, Raya MA, The Past RG. 2018. Present, and future of virtual and augmented reality research: a network and cluster analysis of the literature. Front Psychol. 9. doi:10.3389/fpsyg.2018.02086.

Duncan RW, Freeland AE, Jabaley ME, Meydrech EF. 1993. Open hand fractures: an analysis of the recovery of active motion and of complications. J Hand Surg Am. 18(3):387–394. doi:10.1016/0363-5023(93)90080-M.

Eckert M, Volmerg JS, Friedrich CM. 2019. Augmented reality in medicine: systematic and bibliographic review. JMIR mHealth and uHealth. 7(4): e10967. doi:10.2196/10967.

Ellis B, Bruton A. 2002. A study to compare the reliability of composite finger flexion with goniometry for measurement of range of motion in the hand. Clin Rehabil. 16(5):562–570. doi:10.1191/0269215502cr513oa.

Field MJ, Grigsby J. 2002. Telemedicine and remote patient monitoring. JAMA. 288(4):423–425. doi:10.1001/jama.288.4.423.

Flavián C, Ibáñez-Sánchez S, Orús C. 2019. The impact of virtual, augmented and mixed reality technologies on the customer experience. J Bus Res. 100:547–560. doi:10.1016/j.jbusres.2018.10.050.

Hartley RL, Lam J, Kinlin C, Hulin K, Temple-Oberle C, Harrop AR, Fraulin FOG. 2020. Surgical and nonsurgical pediatric hand fractures: a cohort study. Plast Reconstructive Surg – Global Open. 8(3):e2703. doi:10.1097/GOX.0000000000002703.

Hays PL, Rozental TD. 2013. Rehabilitative strategies following hand fractures. Hand Clin. 29(4):585–600. doi:10.1016/j.hcl.2013.08.011.

Hepping AM, Barvelink B, Ploegmakers JJW, van der Palen J, Geertzen JHB, Bulstra SK, Harbers JS, Stevens M. 2020. Recovery of strength after reduced pediatric fractures of the forearm, wrist or hand; A prospective study. PLOS ONE. 15(4):e0230862. doi:10.1371/journal.pone.0230862.

Kim JS, Kim BK, Jang M, Kang K, Kim D, Ju B-K, Kim J. 2020. Wearable hand module and real-time tracking algorithms for measuring finger joint angles of different hand sizes with high accuracy using FBG strain sensor. Sensors. 20(7):1921. doi:10.3390/s20071921.

Koo TK, Li MYA. 2016. Guideline of selecting and reporting intraclass correlation coefficients for reliability research. J Chiropr Med. 15 (2):155–163. doi:10.1016/j.jcm.2016.02.012.

Kulkov I, Berggren B, Hellström M, Wikström K. 2021. Navigating uncharted waters: designing business models for virtual and augmented reality companies in the medical industry. J Eng Technol Manage. 59:101614. doi:10.1016/j.jengtecman.2021.101614.

Liu W, Anguelov D, Erhan D, Szegedy C, Reed S, Fu CY, Berg AC. 2016. SSD: single shot multibox detector. arXiv:151202325 [Cs]. 9905:21–37. doi:10.1007/978-3-319-46448-0_2.

Lockery D, Peters JF, Ramanna S, Shay BL, Szturm T. 2011. Store-and-feedforward adaptive gaming system for hand-finger motion tracking in telerehabilitation. IEEE Trans Inf Technol Biomed. 15(3):467–473. doi:10.1109/TITB.2011.2125976.

Logan AG, McIsaac WJ, Tisler A, Irvine M, Saunders A, Dunai A, Rizo C, Feig D, Hamill M, Trudel M, et al. 2007. Mobile phone-based remote patient monitoring system for management of hypertension in diabetic patients. Am J Hypertens. 20(9):942–948. doi:10.1016/j.amjhyper.2007.03.020.

Malasinghe LP, Ramzan N, Dahal K. 2019. Remote patient monitoring: a comprehensive study. J Ambient Intell Human Comput. 10(1):57–76. doi:10.1007/s12652-017-0598-x.

Meals C, Meals R. 2013. Hand fractures: a review of current treatment strategies. J Hand Surg Am. 38(5):1021–1031. quiz 1031. doi:10.1016/j.jhsa.2013.02.017.

Miyake K, Mori H, Matsuma S, Kimura C, Izumoto M, Nakaoka H, Sayama K. 2020. A new method measurement for finger range of motion using a smartphone. J Plast Surg Hand Surg. 54(4):207–214. doi:10.1080/2000656X.2020.1755296.

Nanayakkara VK, Cotugno G, Vitzilaios N, Venetsanos D, Nanayakkara T, Sahinkaya MN. 2017. The role of morphology of the thumb in anthropomorphic grasping: a review. Front Mech Eng. doi:10.3389/fmech.2017.00005.

Pham T, Pathirana PN, Trinh H, Fay P. 2015. A Non-Contact Measurement System for the range of motion of the hand. Sensors (Basel). 15 (8):18315–18333. doi:10.3390/s150818315.

Schiefer C, Kraus T, Ellegast RP, Ochsmann E. 2015. A technical support tool for joint range of motion determination in functional diagnostics - an inter-rater study. J Occup Med Toxicol. 10:16. doi:10.1186/s12995-015-0058-5.

Silva R, Oliveira J, Giraldi G Introduction to augmented reality. Published online 2003 Jan 1.

Vegesna A, Tran M, Angelaccio M, Arcona S. 2016. Remote patient monitoring via non-invasive digital technologies: a systematic review. Telemed e-Health. 23(1):3–17. doi:10.1089/tmj.2016.0051.

Yeung AWK, Tosevska A, Klager E, Eibensteiner F, Laxar D, Stoyanov J, Glisic M, Zeiner S, Kulnik ST, Crutzen R, et al. 2021. Virtual and augmented reality applications in medicine: analysis of the scientific literature. J Med Internet Res. 23(2):e25499. doi:10.2196/25499.

Zhang F, Bazarevsky V, Vakunov A, Tkachenka A, Sung G, Chang CL, Grundmann M MediaPipe hands: on-device real-time hand tracking. arXiv:200610214 [cs]. Published online 2020 Jun 17. [Accessed 2021 Apr 5]. http://arxiv.org/abs/2006.10214

Zhao MY, Ong SK, Nee AYC. 2016. An augmented reality-assisted therapeutic healthcare exercise system based on bare-hand interaction. Int J Human–Comput Interact. 32(9):708–721. doi:10.1080/10447318.2016.1191263.