Integrated Smart Glove for Hand Motion Monitoring

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***Abstract*— Developments in Virtual Reality (VR) technology and its overall market have been occurring since the 1960s when Ivan Sutherland created the world's first tracked head-mounted display (HMD) – a goggle type head gear. In society today, consumers are expecting a more immersive experience and associated tools to bridge the cyber-physical divide. This paper presents the development of a next generation smart glove microsystem to facilitate Human Computer Interaction through the integration of sensors, processors and wireless technology. The objective of the glove is to measure the range of hand joint movements, in real time and empirically in a quantitative manner. This includes accurate measurement of flexion, extension, adduction and abduction of the metacarpophalangeal (MCP), Proximal interphalangeal (PIP) and Distal interphalangeal (DIP) joints of the fingers and thumb in degrees, together with thumb-index web space movement. This system enables full real-time monitoring of complex hand movements. Commercially available gloves are not fitted with sufficient sensors for full data capture, and require calibration for each glove wearer. Unlike these current state-of-the-art data gloves, the UU / Tyndall Inertial Measurement Unit (IMU) glove uses a combination of novel stretchable substrate material and 9 degree of freedom (DOF) inertial sensors in conjunction with complex data analytics to detect joint movement. Our novel IMU data glove requires minimal calibration and is therefore particularly suited to the multiple application domains such as Human Computer interfacing, Virtual reality, the healthcare environment.**

Keywords*— *Data glove; IMU; Virtual reality, Arthritis, Joint Stiffness, Hand Monitoring

I. INTRODUCTION

Data gloves contain strategically placed sensors controlled by circuitry that communicates finger joint movement to an end device. In recent years data gloves have been evaluated by researchers as an effective replacement for the universal goniometer (UG) [12]–[17]. Results showed comparable repeatability to the UG with the added advantage of simultaneous angular measurement and removal of intra-tester and inter-tester reliability problems associated with the UG. Data gloves however have several drawbacks; they require laborious calibration, are difficult to don and doff; and are designed to fit specific hand sizes and so require small, medium and large gloves to fit all hand variations. The first iteration of our system was developed using a state-of-the-art 5DT Ultra 14 data glove [18]. In this paper, our inertial measurement unit (IMU) Smart Glove is evaluated against this data glove for accuracy and repeatability and further validated using the Vicon motion capture system [19].

Virtual reality (VR) systems can be segmented into one of three experiences: non-immersive, semi-immersive, and fully immersive. Non-immersive systems would be those that can be visualized on a desktop computer. Semi-immersive VR environments incorporate images projected on the walls (e.g., cave automatic virtual environment, better known by the acronym CAVE). For a period of time, the user may superficially succumb to the perception of "being there", but all the while still be aware of their real world surroundings. Finally, there is fully-immersive technology. In these systems, real-world visual and auditory cues are completely blocked out and the user has a sensory experience of being inside the computer-generated world. The experience is made ever more real through the use of hand-held and/or wearable devices that in some cases deliver haptic feedback which invoke sensations of touch. To enable Human computer interaction in this immersive fashion, high precision data acquisition systems need to be developed which are accurate, require minimal calibration and which provide real-time data streams wirelessly. The development of such a glove based system lends itself to multiple use cases including the Gaming environment and hand healthcare (e.g., Rheumatoid Arthritis (RA) monitoring).

This paper is organized as follows. Section II describes two data glove use case scenarios. Section III describes the glove hardware. Section IV addresses the system implementation. Section V goes into the calibration of the glove. Section VI describes the graphical user interface (GUI). Sections VII and VIII describe the tests and results respectively. Section IX goes into the conclusions. The acknowledgment section closes the paper.

II. MOTION MONITORING GLOVE EXAMPLE USE CASE

Wearable data acquisition systems which provide real time data of high quality are increasingly valuable in a variety of application scenarios. These range from virtual reality, gaming and Human Computer Interaction (HCI) to Connected Health and monitoring of wellness in a clinical context. Two such application spaces are outlined in the following subsections.

A. *Virtual Reality (VR)*

To be compatible with the Virtual Reality use case, it is important that any glove system developed for Human Computer Interaction adheres to requirements detailed below:

1. *Accuracy & Precision*. Accuracy is the degree of closeness to a quantity's actual true value. Precision is the degree to which repeated measurements give the same quantity. Here, we define accuracy and precision to consist of position and orientation. Different parts of the hand should have priority for accuracy: a) The mapping of the center of the virtual hand is the most important for most VR applications, b) The finger tips are the next most important for accuracy as the joints can be estimated via inverse kinematics and other constraints, c) The skeleton/joints of the hand are the next most important for accuracy.
2. *Consistent recognition of gestures*. Like speech recognition, if a gesture recognition system occasionally misinterprets signals then a break in presence occurs and users can become annoyed. Accidental gestures (known as false positives) are also a problem (e.g., accidentally signaling a command when unconsciously “talking with the hands”).
3. *Low latency*. The faster the response of the system, then the more pleasant the user experience and the more easily users can enter a state of flow.
4. *Simulation of button presses*. Some applications will greatly benefit from simulation of button presses that provide a sense of self-haptic feedback (e.g., by touching two fingers together) and to control the game and system.

B. *Rheumatoid Arthritis assessment*

RA is an auto-immune disease which attacks the synovial tissue lubricating skeletal joints and is characterized by pain, swelling, stiffness and deformity. This systemic condition affects the musculoskeletal system, including bones, joints, muscles and tendons that contribute to loss of function and Range of Motion (ROM). Early identification of RA is important to initiate treatment, reduce disease activity, restrict its progression and ultimately lead to its remission. Clinical manifestations of RA can be confused with similar unrelated musculo-skeletal and muscular disorders. Identifying its tell-tale symptoms for early diagnosis has been the long-term goal of clinicians and researchers. Classifiers such as the Disease Activity Score (DAS) and Health Assessment Questionnaire (HAQ) provide an outcome measurement that reflects a patient’s severity of RA disease activity. Such measurements are subjective and can be influenced by other factors such as depression or unrelated non-inflammatory conditions. Traditional objective measurement of RA using the universal goniometer (UG) and visual examination of the hands is labour intensive, open to inter rater and intra-rater reliability problems.

The DAS and HAQ [2] [3] are commonly used to measure disease onset and to assess disease status during clinical assessment [1]. Joint Stiffness is a common condition of RA that affects their ability to perform basic activities and daily functions [4] [5]. Several objective measurement systems have been devised by researchers and assessed in clinical trials for effectiveness as a joint stiffness measurement device [6]–[11].

III. TYNDALL GLOVE HW DESCRIPTION

The objective of the IMU Smart Glove is to measure the range of hand joint movements in a quantitative manner, including flexion, extension, adduction and abduction of the MCP, PIP and DIP joints of the fingers and thumb in degrees, together with thumb-index web space, palmar abduction to assist medical clinicians with the accurate measurement of the common condition of loss of movement in the human hand in patients with arthritis. All the Smart Glove functionality is maintained, controlled and analyzed by our in-house developed software system.

The described glove is a second generation iteration of the system by the authors as described in previous work [20].

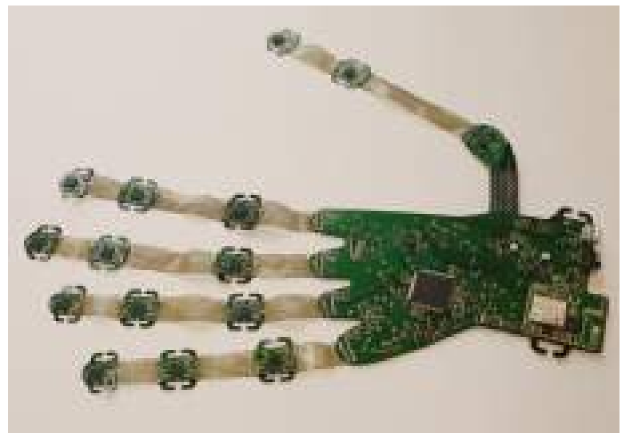

Figure 1. The IMU Smart Glove rev 2

A. *HW description*

The IMU glove, shown in Figure 1, has been manufactured using a mix of stretchable & flexible technology. Stretchable areas of the device cross each finger joint so they can conform to the human hand.

The glove includes 16 9-axes IMU’s (each including 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer) strategically placed to account for the degrees of freedom of each finger joint of the hand. IMUs are positioned on the stretchable interconnect and are located on the phalange of each finger segment to measure their orientation and biomechanical parameters.

Each IMU provides 6-degrees of freedom motion information (3 translational + 3 rotational) and 3D orientation information. By placing an IMU at both sides of each finger joint, (that is one per each finger bone and another one on the palm of the hand), the relative orientation of each IMU is calculated and used to generate angular and velocity movement throughout flexion and extension exercise of each finger joint and to calculate splaying of each finger.

B. *Microcontroller*

The processor selected for use in the system is an AVR32 UC3C 32 Bit Microcontroller. This is a high performance, low power 32-bit AVR microcontroller with built in single precision floating point unit. It was selected to enable complex embedded algorithms focused on motion analysis to be developed for real time low power consumption operation.

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C. Wireless Communication

The RS9110-N-11-22 [21] module shown in Figure 2 is a IEEE 802.11b/g/n WLAN device that directly provides a wireless interface to any equipment with a UART or SPI interface for data transfer. It integrates a MAC, baseband processor, RF transceiver with power amplifier, a frequency reference, and an antenna in hardware. It also provides all WLAN protocols and configuration functionality. A networking stack in embedded in the firmware to enable a fully self-contained 802.11n WLAN solution for a variety of applications.

The module incorporates a highly integrated 2.4 GHz transceiver and power amplifier with direct conversion architecture, and an integrated frequency reference antenna. The RS9110-N-11-22 comes with flexible frameworks to enable usage in various application scenarios including high throughput and more network features.

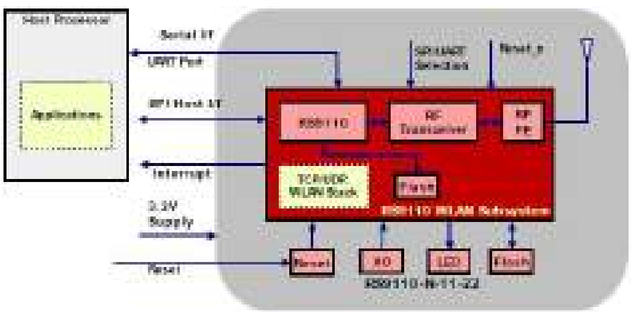

Figure 2. RS9110-N-11-22 System Block Diagram

The system operates according to a low complexity standard 4-wire SPI interface with the capability of operation up to a maximum clock speed of 25MHz. The communications module conforms to IEEE 802.11b/g/n standards and includes hardware accelerated implementation of WEP 64/128-bit and AES in infrastructure and ad-hoc modes. The fact that the module supports multiple security features such as WPA/WPA2-PSK, WEP, TKIP make it compatible with all medical ERP systems.

D. Sensors

The MPU-9150 [22] is a full three axis inertial measurement system incorporating tri-axis angular rate sensor (gyroscope) with sensitivity up to 131 LSBs/dps and a full-scale range of ±250, ±500, ±1000, and ±2000dps, tri-axis accelerometer with a programmable full scale range of ±2g, ±4g, ±8g and ±16g and a tri-axis compass with a full scale range of ±1200µT. The module incorporates embedded algorithms for run-time bias and compass calibration, so no user intervention is required. The MPU-9150 features three 16-bit analog-to-digital converters (ADCs) for digitizing gyroscope outputs, three 16-bit ADCs for digitizing accelerometer outputs, and three 13-bit ADCs for digitizing magnetometer outputs. For precision tracking of both fast and slow motions, the module features a user programmable gyroscope full-scale range of ±250, ±500, ±1000, and ±2000°/sec (dps), a user programmable accelerometer full-scale range of ±2g, ±4g, ±8g, and ±16g, and a magnetometer full-scale range of ±1200µT.

E. Additional Features

To make the system adaptable in operation and compatible with a wide range of use cases outside the immediate application of RA monitoring, the IMU Smart Glove system also incorporates such features as optional storage via a micro SD card**,** battery monitoring and recharge ability, as well as a USB bootloader, USB communication interface, and 15 Analogue inputs for optional resistive sensors (e.g., bend sensors or force sensors). The analogue front end is a buffered voltage divider to enable additional sensing functionality.

IV. SYSTEM IMPLMENTATION

All the system embedded code is implemented using the Atmel Studio 6 IDE. Currently the implementation includes full application code that continuously reads the sensor outputs and wirelessly transmits the data through a TCP socket.

The accuracy of IMU-based real time motion tracking algorithms is highly influenced by sensor sampling rate. Therefore a fundamental design requirement of the IMU Smart Glove was high application throughput to facilitate the development of algorithms using suitable PC SW such as MATLAB C# and Unity. In addition, it was envisaged that once the algorithms would have been fully developed and tested, they would be fully implemented on the embedded platform. This eliminates the requirement for a high throughput device and allows for a low power implementation for example using BLE in a third generation of the glove.

To ensure maximum achievable sampling rates and computation time are compatible with the application scenario envisaged as specified in conjunction with clinical partners regarding signal temporal granularity, it was decided not to share the I2C bus between each of the 16 MPU9150's. Instead, dedicated I2C lines are provided to each one of the sensors and are driven in parallel. This provides the added advantage of ensuring synchronization between all IMU sensors.

A. Case 1 Raw data transmission.

The embedded processor enables multiple modes of operation depending on the use case and degree of data granularity required. Having the wireless system transmitting raw data at the highest achievable data rate is desirable for the development of the analytics as it is more practical to develop them using PC based SW (real time or post processing) and then porting them to the embedded system than develop them directly within the embedded system.

B. Case 2: Transmission of Raw data & information

The wireless system transmits raw data and quaternions/rotation matrix (from gyros) at the highest achievable data rate. Quaternions then will be subject to drift/errors and the analytics to correct for this are implemented within the controlling software. At this stage we have a clear idea of the maximum processing time that could be allocated in the embedding to this task and that is taken into consideration when designing these algorithms.

C. Case 3: Transmission of processed data

With the wireless system with full analytics embedded, the internal sampling rate of the sensors should be kept to a maximum achievable SR, the high wireless data rate might no longer be required.

V. CALIBRATION USING ACCELEROMETRY AND GYROSCOPE

Data glove accuracy and repeatability is affected by the non-linear nature of glove sensor output and any misalignment between the wearers hand and data glove sensor positioning. Data glove sensor calibration improves sensor accuracy and matches the boundaries of each sensor to those of each finger joint. A calibration routine requires the glove wearer to position groups of finger joints such as MCP's and PIP's at specific poses. Each pose places a finger joint group and relevant data glove sensors at their minimum and maximum boundaries. The IMU Smart Glove uses on-board sensors to automatically calibrate each glove sensor, regardless of the wearer's joint flexibility. Each glove accelerometer sensor is sampled when the hand is in a neutral position to calculate finger joint thickness and slope offset, and used during angular calculation. Accelerometers placed on each one of the finger's phalanges provide information with regards to the inclination to gravity of the phalanx. The output response of each sensor provides information on the orientation of the sensor to gravity as shown in Figure 3. The orientation to gravity of each one of the sensors placed on adjacent phalanges can be used to estimate the flexion of the finger.

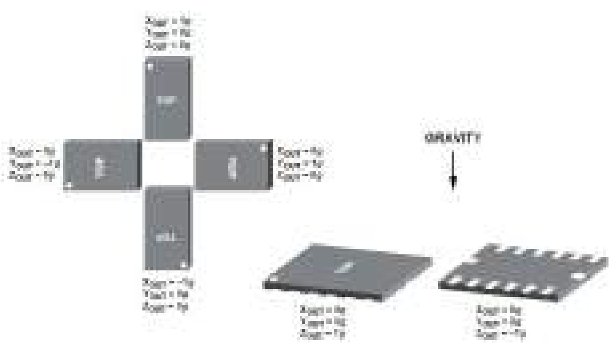

Figure 3. Output response vs. Orientation to gravity

For example, if the measured acceleration for a specific finger from the medial phalanx accelerometer is (Xout, Yout, Zout)= (-1,0,0)g and from the proximal phalanx accelerometer is (Xout, Yout, Zout)= (0,0,1)g, it indicates a flexion of the PIP joint of 90 degrees. The inclination to gravity is determined according to the standard formulas (1), (2) and (3):

$$\theta = \tan^{-1}\left(\frac{A_{X,OUT}}{\sqrt{A_{Y,OUT}^2 + A_{Z,OUT}^2}}\right) \quad (1)$$

$$\psi = \tan^{-1}\left(\frac{A_{Y,OUT}}{\sqrt{A_{X,OUT}^2 + A_{Z,OUT}^2}}\right) \quad (2)$$

$$\phi = \tan^{-1}\left(\frac{\sqrt{A_{X,OUT}^2 + A_{Y,OUT}^2}}{A_{Z,OUT}}\right) \quad (3)$$

Where: θ is the angle between the horizon and the x-axis of the accelerometer, ψ is the angle between the horizon and the y-axis of the accelerometer, and φ is the angle between the gravity vector and the z-axis.

VI. GUI/USER INTERFACE

Data is streamed in real-time according to the use cases outlined above and post processed by our controlling software. A pivotal role of this software is its ability to encapsulate movement associated with finger joints in real time. Figure 4 shows an example of the user interface. Algorithms segment recorded data to extract relevant flexion and extension movement information.

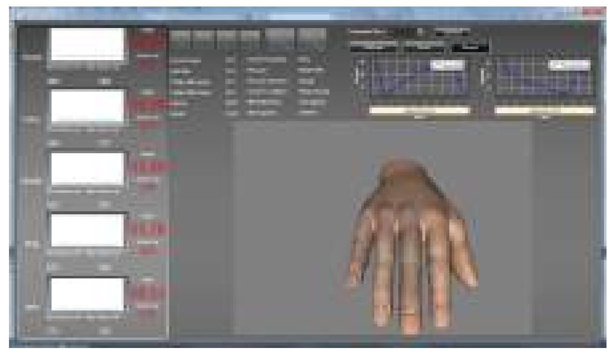

Figure 4. Angular output from the data glove is displayed in 3D

A. Data analytics and Post processing

Each angular calculation is low-pass filtered to remove sensor noise. A complementary filter with error control is implemented to combine accelerometer output with gyroscope rotation angle. Gyroscope rotational angle is initially accurate and drifts over time. Accelerometer angle cannot distinguish between lateral acceleration and rotation. The complementary filter acts as a high-pass and low-pass filter on both signals. It combines estimated gyroscope rotation and accelerometer angle to create an angular output.

VII. TESTING STRATEGIES

Our new data glove was assessed for accuracy and repeatability and was compared with the 5DT state-of-the-art data glove. The Vicon MX motion capture system was used during accuracy testing to independently measure angular values generated at each finger joint. Movement was recorded by Vicon and simultaneously by our in-house developed controlling software whilst each glove was placed on blocks of wood cut to specific angles. Angular readings were assessed using Root Mean Square Error (RMS) to provide an indicator of the variance between each estimated angular repetition value and the expected true value influenced by the angle on each block of wood. RMS error is influenced by both positive and negative errors which are either above or below the expected true value. Therefore RMS output is a measure of the angular error. Repeatability testing examined the ability of each data glove to consistently replicate angular readings when the subjects hand was held in a repeatable position. Testing strategies were originally developed to assess data glove suitability as a replacement for the UG. Although no formal set of repeatability testing strategies exist, the strategies used by [12] have been adopted by subsequent research groups [13] [16] [23]–[26] and are used in this study to allow comparison between study results.

VIII. RESULTS AND DISCUSSION

The 'flat hand' test examines each data glove's ability to maintain a minimum repeatable value after full stretch of each data glove sensor. The plaster mould test examines the ability of each data glove to reproduce angular readings when positioned in a repeatable position. In all tests, our data glove was not calibrated for the subject. The 5DT data glove was calibrated.

A. 'Flat hand' Results

The 'flat hand' test results demonstrated in Table I show that the IMU data glove outperformed the 5DT data glove. Mean MCP readings for the IMU glove were near-perfect -0.38°, with PIP readings of -2.53°. The 5DT produced readings of 4.17° for MCP and 2.27° for PIP. This is particularly impressive since the IMU glove was not calibrated before use.

TABLE I. COMPARISON OF MEAN ANGULAR READINGS RECORDED DURING 'FLAT HAND' TESTING

	5DT (Angle / SD)	IMU (Angle / SD)
Index MCP	2.34 (1.59)	-0.59 (1.87)
Index PIP	2.04 (1.05)	-2.74 (0.90)
Middle MCP	5.9 (0.55)	1.32 (2.26)
Middle PIP	3.27 (1.13)	-2.94 (1.25)
Ring MCP	5.14 (0.59)	-2.33 (1.21)
Ring PIP	1.02 (0.52)	-2.7 (1.11)
Little MCP	3.32 (0.88)	0.07 (2.56)
Little PIP	2.76 (1.32)	-1.75 (1.31)
Mean MCP	4.17 (0.90)	-0.38 (1.98)
Mean PIP	2.27 (1.0)	-2.53 (1.14)
Overall mean	3.22 (0.95)	-1.46 (1.56)

B. Plaster mould test results

Table II shows comparison results for plaster mould testing for the 5DT and our IMU data glove. Readings showed the IMU Smart Glove produced better repeatability for MCP and PIP joints and better overall repeatability as indicated by the lower mean range angular reading.

TABLE II. COMPARISON OF MEAN RANGE AND SD READINGS FROM PLASTER MOULD TESTING FOR EACH DATA GLOVE

Glove	MCP		PIP		Mean	
	Range	SD	Range	SD	Range	SD
5DT	8.85	2.13	6.23	2.09	7.54	2.11
IMU	5.99	1.89	5.10	1.58	5.55	1.74

C. Accuracy results

Table III shows comparison of results for the 5DT and our IMU Smart Glove compared with the Vicon motion capture system and the UG. Results showed the goniometer had greatest overall accuracy of 93.23% with overall RMS of 2.76°. This is in agreement with typical findings on goniometric accuracy with 95% of intratester reliability within 5° of measurement and intertester reliability in the range of 7° to 9° [27]–[29]. The Vicon system provided mean accuracy of 89.33% with RMS of 5.19°.

TABLE III. MEAN ACCURACY PERCENTAGE FOR EACH SENSOR INCLUDING MEAN ERROR AND OVERALL ACCURACY PERCENTAGE

Sensor	Vicon	5DT	Goniometer	IMU
Index MCP	93.31	94.20	97.95	89.57
Index PIP	91.23	92.01	90.75	91.47
Middle MCP	91.46	79.66	95.83	82.40
Middle PIP	84.08	74.97	88.96	77.29
Ring MCP	87.20	70.46	97.37	82.02
Ring PIP	86.99	91.99	90.70	89.51
Little MCP	86.14	85.83	91.28	83.38
Little PIP	94.23	74.56	93.03	86.27
Overall accuracy %	**89.33**	**82.96**	**93.23**	**85.24**
RMS	**5.19**	**7.15**	**2.76**	**5.95**

This inaccuracy was most likely caused by noise, marker occlusion, and distance of reflective markers from cameras. The IMU data glove provided the best accuracy measurement of all data gloves and demonstrated similar accuracy to the Vicon measurement system. The RMS results obtained show that readings obtained from sensors contained approximately 5.95° of error. Results shown in Table III indicate that all sensors demonstrated accuracy between 82% to 91% except for the Middle PIP sensor that had accuracy of 77.29%.

D. Comparison with previous trials

The results shown in Table IV compare 'flat hand' and plaster mould tests for the 5DT and our IMU data glove with previous research studies involving data gloves. The 5DT data glove demonstrated range readings that out-performed data glove findings by [12] [13] and were similar to [26]. The data glove examined by [15] provided better results than all studies including the 5DT and our IMU glove. However this glove contained only 5 sensors that recorded movement of the MCP joints. The IMU glove performed better than all other data glove studies. Readings recorded by earlier studies are averaged for several subjects. This can hide higher inaccurate results for some subjects. For example, [12] recorded range readings from 5 subjects that varied between 2.5° to 6.7°. Results were averaged to 4.4°. Similarly, results from 'flat hand' testing from the study by [13] were summarised from a group of 6 male and female participants. Mean male range results went from 2.37° to 5.49° and mean female from 3.90° to 4.75°.

TABLE IV. COMPARISON OF 'FLAT HAND' AND PLASTER MOULD TESTS WITH PREVIOUS DATA GLOVE STUDIES

Study	Flat hand test (Range / SD)	Plaster mould test (Range / SD)
Wise et al. [12]	4.4 (2.2)	6.5 (2.6)
Dipietro et al. [13]	3.84 (1.23)	7.47 (2.44)
Simone et al. [15]	1.49 (0.5)	5.22 (1.61)
Gentner and Classen [26]	2.61 (0.86)	6.09 (1.94)
5DT (this study)	2.27 (0.995)	7.54 (2.11)
IMU (this study)	4.86 (1.56)	5.55 (1.74)

IX. CONCLUSIONS

Data gloves have been proven to be a viable replacement for the UG and can offer unbiased finger joint ROM measurement. However their dependence on calibration reduces their usefulness in the many application spaces. The novel IMU based wireless Smart Glove detailed in this paper removes the requirement for sensor calibration using accelerometers and gyroscopes teamed with intelligent software techniques. Test results showed our IMU data glove had comparable repeatability to the UG with the added advantage of simultaneous angular measurement and removal of intra-tester and inter-tester reliability. Accuracy testing results showed the IMU data glove provided better accuracy and less overall error than the 5DT data glove with which it was compared. Of Note the IMU glove required no calibration before use whilst maintaining results which demonstrated it had similar accuracy to the Vicon system.

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