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Novel Smart Glove Technology as a Biomechanical Monitoring Tool

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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 multiple application domains such as Human Computer interfacing, Virtual reality, the healthcare environment.

Keywords: Data glove, IMU, Virtual reality, Arthritis, Joint Stiffness, Hand Monitoring.

1. 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
The objective of our IMU Smart Glove is to quantitatively measure finger joint ROM 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 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].

![Fig. 1. The IMU Smart Glove rev 2.](image)

### 2.1. System HW Description

The IMU glove, shown in Fig. 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 (DOF) 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 orientation and biomechanical parameters.

Each IMU provides 6 DOF 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.

### 2.2. Microcontroller

The processor selected for use in the system is an Atmel 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.

### 2.3. Wireless Communication

The module selected for use in the system is the RS9110-N-11-22 [21] module shown in Fig. 2. This module is an 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 is 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 scenarios including high throughput networking applications.

![Fig. 2. RS9110-N-11-22 System Block Diagram.](image)

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 module supports multiple security features such as WPA/WPA2-PSK, WEP, TKIP which makes it compatible with all medical ERP systems.
2.4. 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 ±2000 dps, tri-axis accelerometer with a programmable full scale range of ±2 g, ±4 g, ±8 g and ±16 g and a tri-axis compass with a full scale range of ±1200 μT. This 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 ±2 g, ±4 g, ±8 g, and ±16 g, and a magnetometer full-scale range of ±1200 μT.

2.5. 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 facility, 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.

2.6. Flex Technology

The IMU Smart Glove PCB is a combination of flexible and stretchable PCB technology [33]. The stretchable material enables the microsystem to closely replicate mechanical properties of the human hand more accurately than standard flexible technology. As shown in Fig. 3, stretchable PCB sections are incorporated on hand areas crossing several finger joints to enable flexion at the knuckles and provide an interconnect mechanism between the “islands” of rigid PCB substrates which incorporate the WIMU technology.

The stretchable PCB technology is available from the company “Q.P.I. Group”. The substrate material is polyurethane. It is possible to obtain a stretch factor of up to 30% to enable wearable sensor system interconnect, depending on the design implemented on the copper pattern.

3. System Implementation

All the system embedded code is implemented using the Atmel Studio 6 IDE. Currently the implementation includes full application code that continuously reads sensor outputs and wirelessly transmits their 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 potential 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.

3.1. 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.

3.2. Case 2. Transmission of Raw Data and 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.

3.3. 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.

The processing time (per sample cycle) allocated to the embedded tasks and estimated maximum sampling rate / Application Throughput with the microcontroller running at 48 MHz are shown in table I Depending on the computational complexity of the drift correction algorithm, (which are under development at the Tyndall Institute), different application data throughputs are achievable as shown in Table 1.

<table>
<thead>
<tr>
<th>Table 1. Processing time requirements for motion data analysis.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sensor Sampling (16 IMUs)</strong></td>
</tr>
<tr>
<td>--------------------------------</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Wireless Communications</strong></td>
</tr>
<tr>
<td><strong>Quaternions / Rotation Matrix Algorithm</strong></td>
</tr>
<tr>
<td><strong>Drift correction algorithms</strong></td>
</tr>
<tr>
<td><strong>Estimated application throughput/data rate</strong></td>
</tr>
</tbody>
</table>

3.4. Calibration using Accelerometry and Gyroscope Datasets

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 Fig. 4. The orientation to gravity of each one of the sensors placed on adjacent phalanges can be used to estimate the flexion of the finger.

![Fig. 4. Output response vs. Orientation to gravity](image)

For example, if the measured acceleration for a specific finger from the medial phalanx accelerometer is \((X_{\text{out}}, Y_{\text{out}}, Z_{\text{out}}) = (\text{-1,0,0}) \text{ g}\) and from the proximal phalanx accelerometer is \((X_{\text{out}}, Y_{\text{out}}, Z_{\text{out}}) = (0,0,1) \text{ g}\), 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):

\[
\theta = \tan^{-1} \left( \frac{A_{x,\text{out}}}{\sqrt{A_{y,\text{out}}^2 + A_{z,\text{out}}^2}} \right) \quad (1)
\]

\[
\psi = \tan^{-1} \left( \frac{A_{y,\text{out}}}{\sqrt{A_{x,\text{out}}^2 + A_{z,\text{out}}^2}} \right) \quad (2)
\]

\[
\phi = \tan^{-1} \left( \frac{A_{z,\text{out}}}{A_{x,\text{out}}^2 + A_{y,\text{out}}^2} \right) \quad (3)
\]

where \(\theta\) is the angle between the horizon and the x-axis of the accelerometer, \(\psi\) is the angle between the horizon and the y-axis of the accelerometer, and \(\phi\) is the angle between the gravity vector and the z-axis.

3.5. GUI/User Interface

Data is streamed in real-time according to the use cases outlined above and post processed by our controlling software. This software is called
’DigitEase’ [34] shown in Fig. 5. A pivotal role of DigitEase is its ability to encapsulate movement associated with finger joints in real time. Fig. 5 shows an example of DigitEase’s user interface.

![DigitEase User Interface](image1.png)

Fig. 5. Angular output from the data glove is displayed in 3D.

Algorithms segment recorded data to extract relevant flexion and extension movement information. Each piece of sensor data is categorised into pre-repetition, flexion, sustain, extension and post-repetition movement.

Fig. 6 demonstrates a typical flexion and extension angular movement profile used by DigitEase. Segmentation of finger joint movement is required to isolate flexion and extension movement data from unrequired pre-rep, port-rep and sustain time. Flexion and extension movement is analysed for initial and final angles. Both values represent minimum and maximum ROM information for movement repetitions and are indicators of completion and initialisation of flexion and extension movement.

DigitEase’s data analysis dashboard presents post-segmented patient movement information. Fig. 7 shows an example of the dashboard.

The dashboard displays summary information on patient-completed exercise routines. It details individual repetitions and constituent sub-elements for each exercise routine. Colour coding of each repetition segment indicates performance information. Line charts graphically depict velocity, angle-angle and relative phase information for individually selected repetitions.

![Segmentation of Finger Joint Movement](image2.png)

Fig. 6. Chart demonstrating segments that characterise segmentation of finger joint movement.
4. 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.

4.1. Algorithms for Joint Angle Estimation

Fig. 8 shows the joints of the hand along with their number of degrees of freedom. The joint angles can be calculated as the result of the relative orientation of adjacent phalanges one to another so the algorithms to estimate the joints angles from the IMUs are based on the orientation estimation of the sensors themselves. This orientation is commonly represented by quaternions. Equations (4) - (7) represent the orientation / quaternions of adjacent phalanges that are linked by each joint.

\[
q_{\text{palm},j} = q_{\text{palm}}
\]

(4)

\[
q_{\text{MCP},j} = q_{\text{palm}}^{-1} \times q_{\text{MCP}}
\]

(5)

\[
q_{\text{PIP},j} = q_{\text{MCP}}^{-1} \times q_{\text{PIP}}
\]

(6)

\[
q_{\text{DIP},j} = q_{\text{PIP}}^{-1} \times q_{\text{DIP}}
\]

(7)

Over the years, a variety of algorithms for the estimation of orientation have been developed. The majority of these are quaternion-based algorithm and they can be divided in three main approaches: a) the deterministic approach (least-squares), b) the frequency–based approach (Complementary Filter) and c) the stochastic (Kalman filtering).

The deterministic approach was originally introduced in 1965, in the so-called Wahba’s problem [30], which is a constrained least-squares optimization problem for finding the rotation matrix between two coordinate systems from a set of weighted vector measurements. Some of such algorithms are the TRIAD (Tri-axial Attitude Determination), QUEST (Quaternion ESTimator) and FQA (Factored Quaternion Algorithm). These algorithms are based on the concept of vector matching and require measurements of constant reference vectors.

The frequency–based approach fuses the orientation estimated from accelerometers and
magnetometers with the orientation estimated from 
gyroscopes with a complementary filter. This filter 
blends the static low-frequency information provided 
by accelerometers and magnetometers, and the 
dynamic high frequency information provided by 
gyroscopes. The aim of the complementary filter is 
to ensure a compromise between the accuracy provided 
by short-term integration of the gyroscope data and the 
long-term measurements precision obtained by the 
accelerometer and magnetometer [31].

Stochastic estimation algorithms use a dynamic model 
for predicting aspects of the time behaviour of a 
system and a measurement model in order to produce 
the most accurate estimate possible of the system state. Among 
all stochastic algorithms, the Kalman filter is one of the most 
often used algorithms for tasks that involve multisensory fusion, 
filtering and motion prediction [32]. The filter works in a two-step 
process consisting of a prediction step and an update step. In the 
prediction step, Kalman filter produces estimates of the 
current state variables, along with their 
uncertainties. Once the outcome of the next 
measurement (corrupted with error and noise) is 
observed, these estimates are updated using a 
weighted average. Because of the algorithm’s 
recursive nature, it can run in real time using only the 
present input measurement and the previously 
calculated state and its uncertainty matrix.

5. Testing Strategies and Results

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 DigitEase 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 hands 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.

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.

5.1. ‘Flat Hand’ Results

The ‘flat hand’ test results demonstrated in Table 2 
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. The results for our IMU glove are based 
on a system which is not calibrated before use.

Table 2. Comparison of mean angular readings 
recorded during ‘flat hand’ testing.

<table>
<thead>
<tr>
<th></th>
<th>5DT (Angle / SD)</th>
<th>IMU (Angle / SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index MCP</td>
<td>2.34 (1.59)</td>
<td>-0.59 (1.87)</td>
</tr>
<tr>
<td>Index PIP</td>
<td>2.04 (1.05)</td>
<td>-2.74 (0.90)</td>
</tr>
<tr>
<td>Middle MCP</td>
<td>5.9 (0.55)</td>
<td>1.32 (2.26)</td>
</tr>
<tr>
<td>Middle PIP</td>
<td>3.27 (1.13)</td>
<td>-2.94 (1.25)</td>
</tr>
<tr>
<td>Ring MCP</td>
<td>5.14 (0.59)</td>
<td>-2.33 (1.21)</td>
</tr>
<tr>
<td>Ring PIP</td>
<td>1.02 (0.52)</td>
<td>-2.7 (1.11)</td>
</tr>
<tr>
<td>Little MCP</td>
<td>3.32 (0.88)</td>
<td>0.07 (2.56)</td>
</tr>
<tr>
<td>Little PIP</td>
<td>2.76 (1.32)</td>
<td>-1.75 (1.31)</td>
</tr>
<tr>
<td>Mean MCP</td>
<td>4.17 (0.90)</td>
<td>-0.38 (1.98)</td>
</tr>
<tr>
<td>Mean PIP</td>
<td>2.27 (1.10)</td>
<td>-2.53 (1.14)</td>
</tr>
<tr>
<td>Overall mean</td>
<td>3.22 (0.95)</td>
<td>-1.46 (1.56)</td>
</tr>
</tbody>
</table>

5.2. Plaster Mould Test Results

Table 3 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. Comparison of mean range and 
SD readings from plaster mould testing for each data 
glove.

Table 3. Plaster mould test results.

<table>
<thead>
<tr>
<th>Glove</th>
<th>MCP</th>
<th>PIP</th>
<th>Mean</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Range</td>
<td>SD</td>
<td>Range</td>
<td>SD</td>
</tr>
<tr>
<td>5DT</td>
<td>8.85</td>
<td>2.13</td>
<td>6.23</td>
<td>2.09</td>
</tr>
<tr>
<td>IMU</td>
<td>5.99</td>
<td>1.89</td>
<td>5.10</td>
<td>1.58</td>
</tr>
</tbody>
</table>

5.3. Glove Finger Position Accuracy Results

Table 4 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°. Mean accuracy percentage for each sensor including mean error and overall accuracy percentage.

Table 4. Comparison between Tyndall WIMU Glove and 5DT Glove.

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

This inaccuracy was most likely caused by noise, marker occlusion, and distance of reflective markers from Vicon cameras. Our IMU data glove provided best accuracy measurement of both data gloves and demonstrated similar accuracy to the Vicon measurement system. RMS results show that readings obtained from sensors contained approximately 5.95° of error. Results shown in Table 3 indicate that all sensors demonstrated accuracy between 82 % to 91 % except for the Middle PIP sensor that had accuracy of 77.29 %. This decreased accuracy may have been caused by slight stretch of sensor cable for this particular sensor.

### 5.4. Comparison with Previous Trials

The results shown in Table 5 compare ‘flat hand’ and plaster mould tests for the 5DT and our IMU data glove with previous research studies involving data gloves.

Table 5. Comparison of ‘flat hand’ and plaster mould tests with previous data glove studies.

<table>
<thead>
<tr>
<th>Study</th>
<th>Flat hand test (Range / SD)</th>
<th>Plaster mould test (Range / SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wise et al. [12]</td>
<td>4.4 (2.2)</td>
<td>6.5 (2.6)</td>
</tr>
<tr>
<td>Dipietro et al. [13]</td>
<td>5.84 (1.23)</td>
<td>7.47 (2.44)</td>
</tr>
<tr>
<td>Simone et al. [15]</td>
<td>1.49 (0.5)</td>
<td>5.22 (1.61)</td>
</tr>
<tr>
<td>Gentner and Classen [26]</td>
<td>2.61 (0.86)</td>
<td>6.09 (1.94)</td>
</tr>
<tr>
<td>5DT (this study)</td>
<td>2.27 (0.995)</td>
<td>7.54 (2.11)</td>
</tr>
<tr>
<td>IMU (this study)</td>
<td>4.86 (1.56)</td>
<td>1.74</td>
</tr>
</tbody>
</table>

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°.

### 6. 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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### References


