A Smartphone-Centric System for the Range of Motion Assessment in Stroke Patients

Wang Wei Lee, Shih-Cheng Yen, Arthur Tay, Ziyi Zhao, Tian Ma Xu, Karen Koh Mui Ling, Yee-Sien Ng, Effie Chew, Angela Lou Kuen Cheong, and Gerald Koh Choon Huat

Abstract—The range of motion (ROM) in stroke patients is often severely affected. Poststroke rehabilitation is guided through the use of clinical assessment scales for the rROM. Unfortunately, these scales are not widely utilized in clinical practice as they are excessively time-consuming. Although commercial motion-capture systems are capable of providing the information required for the assessments, most systems are either too costly or lack the convenience required for assessments to be conducted on a daily basis. This paper presents the design and implementation of a smartphone-based system for automated motor assessment using low-cost off-the-shelf inertial sensors. The system was used to automate a portion of the upper-extremity Fugl–Meyer assessment (FMA), which is widely used to quantify motor deficits in stroke survivors. Twelve out of 33 items were selected, focusing mainly on joint angle measurements of the upper body. The system has the ability to automatically identify the assessment item being conducted, and calculate the maximum respective joint angle achieved. Preliminary results show the ability of this system to achieve comparable results to goniometer measurements, while significantly reducing the time required to conduct the assessments. The portability and ease-of-use of the system would simplify the task of conducting range-of-motion assessments.

Index Terms—Body sensor networks, mobile nodes, patient rehabilitation, wearable sensors.

I. BACKGROUND

STROKE is the fourth leading cause of death in the United States, with about 795,000 people experiencing stroke each year [1]. Globally, an estimated 15 million people suffer stroke yearly [2]. In Singapore, stroke is a major cause of death, with more than 10,000 new patients being hospitalized due to stroke each year [3]. Stroke affects a person’s cognitive, language, perceptual, sensory, and motor abilities [4]. The recovery process is very long, extending beyond the hospital stay and into the home setting, and are guided by clinical assessments such as their range of motion. Accurate assessment of their ranges is hence crucial in selecting the best therapies for stroke patients.

The Fugl–Meyer assessment of sensorimotor recovery after stroke (FMA) is widely used in clinical trials to quantify motor deficits in patients after stroke [5]. The main evaluation aspects of the FMA include motor movements, balance, sensation, joint ROM and pain, thus providing a concise scale to quantify stroke severity with sound psychometric properties. However, the FMA is rarely used in clinics due to its lengthy administration time, as it consists of a 33-item upper extremity subscale and a 17-item lower extremity subscale [6]. A typical full-scale assessment would require more than an hour to conduct. A shorter version of the FMA (S-FM) was developed by Hsieh et al. [7] to reduce its administration time. Despite the reduction in items, the S-FM is still not very widely used. One of the reasons is that the S-FM is still based on observations of subjects’ motor behavior, and measurements are conducted manually using a goniometer or visual estimation. As a result, the accuracy and consistency may vary greatly across clinicians [8]. A precise, reliable, yet convenient method of performing such assessments is thus imperative, and this is where the use of electronic tools may be useful.

The first step to such an effective electronic assessment tool is the ability to accurately measure joint ROM. Traditionally, electronic assessments of ROM are performed using multicamera vision systems, which are often too elaborate, expensive, and inconvenient to perform on large numbers of patients. Other vision-based systems such as Microsoft Kinect have seen significant adoption in applications for posture and gesture detection. However, such systems suffer from skeletal merging [9] and thus do not work reliably when the caregiver is within the field of view of the camera, or if the subject were to sit on a wheelchair/bed. In recent years, there have been a growing number of attempts to track movements in humans using wearable devices instead [10]. Methods such as e-textiles [11], optical linear encoders [12], and fiber optics [13] have been investigated with the aim of providing accurate joint angle measurements. However, these approaches require the calibration of equipment for individual patients, due to the variations in joint sizes and skin elasticity. Inertial measurement units (IMU) are less sensitive to such variations, since they work by comparing orientation between limbs, instead of measuring the amount...
of bend at a joint. In IMU systems, MEMS (microelectromechanical systems) sensors such as accelerometers, gyroscopes, magnetometers or a combination of them are used to estimate the orientation of the limbs the sensors are attached to. Estimation of joint angles and joint kinematics using IMUs have been extensively studied [14]–[18]. The accuracy and reliability of IMU-based systems have since improved to the point where applications in motion capture, gait, and posture analysis are also possible [19], [20], and commercial motion capture systems are now readily available [21], [22].

Despite the availability of technology for accurate joint motion capture, a convenient, user-friendly and cost-effective motor ability assessment tool has yet to appear. Many of the systems mentioned are rather complicated, requiring skilled personnel to operate. In addition, these systems often require a PC to process the data from the sensors, which translates to reduced portability and convenience.

The aim of this paper is to introduce a new joint-angle measurement system, designed specifically for physicians to conduct ROM assessments quickly and easily within the hospital. Although it is also based on IMUs, the system is operated from a smartphone instead, thus improving its mobility. As a start, 12 simple assessment activities from the upper extremity FMA that do not involve muscle-group synergies were selected and implemented in the system. These activities can be automatically identified and measured by the system, thus ensuring that the interface remains simple and user friendly. Developed in collaboration with healthcare professionals from Singapore General Hospital (SGH) and Ang Moh Kio-Thye Hwa Kwan community Hospital (AMKH), the system aims to provide doctors and therapists with a practical tool to perform ROM measurements.

Section II will elaborate on the design and implementation considerations of the system. Section III focuses on validating the accuracy of the system against the goniometer, while Sections IV and V present the discussion and conclusions, respectively.

II. DESIGN AND DEVELOPMENT

A. System Architecture

There are two main parts to the system (see Fig. 1)—the sensor nodes (see Fig. 2) and the application. The sensor nodes are responsible for acquiring data on the orientation and movement of the patient’s limbs. A total of seven sensor nodes are used. Each node includes tri-axial accelerometer, gyroscope, and magnetometer sensors that are polled by an on-board microcontroller. Also included is a wireless communication module and battery. Each node measures 66.6 mm × 28.2 mm × 18.1 mm and weighs 22 g. When used with a fully charged battery, each node lasts 179 min on average.

A sensor-fusion algorithm runs on each node, where raw sensor readings are combined to continuously update the 3-D orientation of the sensor. Compared to implementing the fusion algorithm on the smartphone, calculations performed on individual nodes greatly reduce the computational load on the smartphone, while improving reliability of the orientation estimates since it does not have to deal with the possible loss of sensor readings during wireless transmission.

The IEEE 802.15.4 [23] standard for wireless communication is used for all nodes, in order to reduce size and power consumption. A single larger node capable of communicating on both WiFi and the IEEE 802.15.4 standard is included in the system. Known as the master node, it acts as a bridge between the other (slave) nodes and the smartphone, while at the same time collecting data from its on-board sensors. This eliminates the need for a separate network adapter for the phone. Another advantage of this solution is the distribution of processing load, as the master node encapsulates the network protocol needed to communicate with the rest of the slave nodes. The architecture of the sensor layer is illustrated in Fig. 3.

The application layer runs on an Android smartphone. It receives the orientation of all nodes from the master node via WiFi, from which the posture of the subject can then be derived. The computation of joint angles and the identification of assessment exercises are performed at this stage. The application also serves as the user interface of the system.

B. System Configuration

The system is built using commercially available components. Each slave node consists of an 8 bit microprocessor (ATMEGA328, Atmel), a triaxial accelerometer (ADXL345, Analog Devices), a triaxial gyroscope (ITG3200, InvenSense), a triaxial magnetometer (HMC5883L, Honeywell), as well as a IEEE 802.15.4 compliant wireless module (XB24-A, Digi). The master node uses a different microprocessor (LPC1768, NXP), and also includes a WiFi module (RN-131C, Roving Networks) in addition to the sensors used on the slave nodes.
Fig. 3. Sensor-layer architecture in detail.

Fig. 4. Placement of nodes on a patient. (a) Back. (b) Upper Arm. (c) Lower Arm. (d) Wrist.

Fig. 5. Pipelined data transmission.

MSM7227) and 384 MB of RAM, both of which operate on version 2.2 (Froyo) of the Android operating system.

The system is configured to sample at 25 Hz, which is more than sufficient to capture a stroke patient’s motion activities because of the degraded motor function. 25 Hz is also sufficient for detecting abnormal tremors [24], although this feature was not yet implemented. The sampling rate was limited by the wireless bandwidth (IEEE:802.15.4) available.

C. Communication

A star network topology is adopted for internodal wireless communication, where the master node maintains a direct communication link to the slave nodes.

In order to minimize data loss due to wireless packet collisions, time divisional multiple access (TDMA) is implemented by an application layer protocol (See Fig. 5). Under this scheme, beacon signals are broadcast by the master node to demarcate the boundaries of each period. Each period consists of multiple time slots reserved for slave nodes to transmit data. Hardware timer and serial interrupts are used to ensure that all slave nodes adhere to strict timing constraints, transmitting only within their predefined time slots. With this implementation in place, the system has been tested to be capable of interfacing up to seven slave nodes at 25 Hz, with minimal data loss from packet collision. This was later verified using time stamps on samples from experiments performed on patients. An average of 3.5% of packets were lost per session, while the average time between consecutive samples was 40 ms.

D. Orientation Sensing

Data fusion of the readings from the accelerometer, gyroscope, and magnetometer provides consistent orientation estimates while reducing gyroscope drift, as well as measurement noise from the accelerometer and magnetometer [25]. While many commercial orientation sensors adopt the Kalman filter due to its accuracy and effectiveness [26], they can be
difficult to implement and require high sampling rates. To reduce the computational load, we adopted the algorithm by Sebastian Madgwick [25] which has been tested to be comparable to a proprietary Kalman-based filter used in a commercial IMU-based motion capture product. The main advantage of the algorithm is its low computational demands, and the ability to operate on low sampling rates. This enables orientation estimates to be calculated on the nodes itself, thus reducing the computational tasks of the smartphone application.

The system uses quaternions [27] to describe the estimated orientation of the sensor. Not only is it a more compact representation compared to discrete cosine matrices, it also avoids the problem of gimbal lock when the pitch reaches ±90° (as compared to Euler Angles) [27].

To relate the sensor frame to Earth frame of reference for comparison, vectors representing the x-, y-, and z-axis components in the sensor frame were multiplied by the discrete cosine matrix (DCM) derived from the quaternion output of the algorithm. Equation (1) describes the formula to obtain the DCM for converting from sensor frame to Earth frame, where \( q_0 \) to \( q_3 \) are elements of the quaternion.

\[
\text{DCM} = \begin{bmatrix}
2q_0^2 - 1 + 2q_1^2 & 2(q_1q_2 - q_0q_3) & 2(q_1q_3 + q_0q_2) \\
2(q_1q_2 + q_0q_3) & 2q_2^2 - 1 + 2q_3^2 & 2(q_2q_3 - q_1q_0) \\
2(q_1q_3 - q_0q_2) & 2(q_2q_3 + q_1q_0) & 2q_3^2 - 1 + 2q_0^2 
\end{bmatrix}
\]

Equation (1).

To evaluate the accuracy of the system, the sensor-fusion algorithm was tested against a 10 camera Vicon Bonita optical system (accuracy ± 0.5 mm). A sensor node was strapped onto the Active Wand provided by the manufacturer, which is a rigid structure with optical markers meant for calibration [See Fig. 6(a)]. The sampling rate of the optical system was set to 200 Hz, while signal acquisition and computation of angles was performed using Vicon Tracker software version 1.3.1. The quaternion output from the sensor node was computed at 25 Hz and conversion to angles was performed offline. For comparison, the output from the Vicon system was downsampled to match the system output.

Before each test, the wand was left stationary for 10 s for the algorithm to converge. This initial position was also used to offset between the optical system’s coordinate frame and Earth frame as computed by the sensor. The wand was then offset along the x-axis of the Earth frame, followed by another offset on the x-axis in the opposite direction, beyond the initial position. Such movements were repeated at least 15 times for each axis with offset magnitudes within ±90°. The maximum angular velocity during movement was always below 360°/s. All movements were conducted by hand.

The root-mean-squared error was computed on the difference between the two systems, and results were tabulated in Table I. The error was found to be within 5° in all the three planes of interest. This was higher than the error reported in [25], possibly due to the much lower sampling rate used (25 Hz versus 512 Hz) as well as magnetic interference from the circuitry within the Active Wand. Nevertheless, this performance should be sufficient for our application.

### Table I

<table>
<thead>
<tr>
<th>Plane</th>
<th>Heading</th>
<th>Pitch</th>
<th>Roll</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average RMSE</td>
<td>4.52°</td>
<td>4.08°</td>
<td>3.71°</td>
</tr>
</tbody>
</table>

Fig. 6. Comparison with Vicon system. (a) Attaching a sensor (circled) to the Active Wand (b) Typical output from both systems.

### E. User Interface

1) **Design Criteria**: Central to the system is the user interface (UI), and one important requirement is its usability. Therapists often have to pay full attention to guiding and supporting their patients during the assessments, and thus cannot afford to spend much time setting up and operating a system.

Another requirement mentioned is the flexibility of the software during operation. The therapist should not be forced to conduct the assessment exercises in a predefined order, as depending on the current posture of the patient, the therapist may want to start with the most convenient assessment exercise first.

Taking the above factors into account, the system adopts a very minimalist UI. Only crucial information is displayed on the screen, and large fonts are used to render them. In most cases, only one button is needed to conduct the full assessment. Audio cues are used to indicate to the therapist when a measurement is obtained, thus reducing the need to constantly look at the smartphone during the assessment.

2) **Automatic Exercise Detection**: One innovative feature of the UI is an activity detection algorithm. This feature eliminates the need for the user to scroll through a long list to select different exercises, while still allowing the user to conduct the assessment in any order.

The algorithm works by comparing the initial and final orientation of the limbs. While most exercises (e.g., shoulder flexion, extension, abduction) involve the measurement of an angle with respect to a fixed reference (e.g., gravity vector), some exercises, such as wrist ulnar deviation, involve the measurement of the angle between the starting and ending positions. As such, there is a need to manually indicate to the system when the subject has adopted the starting position. A system of neutral postures was thus introduced. Neutral postures are postures that a subject has to adopt at the beginning of each assessment exercise. The orientation of the sensors in each neutral posture corresponds to the starting position for the exercise, thus providing a reference from which the end position will be measured against (See Fig. 7). Note that Neutral 0 is optional as the computation of joint ROM for each of the activities do not require the initial
angle to be known. However, adopting Neutral 0 at the beginning of an activity would still improve detection accuracy, as the number of possible activities would be reduced. Note that the neutral positions adopted here are not the ones that are commonly used in the FMA [5], [7]. These neutral positions were adopted primarily to make it easier for us to measure the range of motion of different joints.

The logic used in activity detection is based on a set of experimentally derived thresholds, and guided by the patient’s posture at the start of the activity. Fig. 8 illustrates the logic flow. For example, a patient starting in neutral posture 2 who flexes his/her wrist downward would be recognized as performing the wrist-flexion assessment.

The algorithm has been kept intentionally simple considering the limited processing capability of mobile phones, although the accuracy should improve with further refinement and better hardware.

3) Operation: The smartphone has to enable WiFi hotspot mode to connect to the master node. The master node searches for the pre-defined SSID of the hotspot when turned on. To establish the connection, the user has to press the Connect button after the application is launched [See Fig. 9(a)].

Before the assessment begins, the user has to enter the identification of the patient. The user is then taken to the assessment interface once the ID is entered. Within the assessment interface, there is only a single toggle button to start and stop the activity. The subject should adopt the respective neutral posture before the start button is pressed. Automatic activity detection begins once the start button is pressed. Once the application recognizes the activity, a ‘beep’ sound is played, while it continuously calculates the respective joint angle [see Fig. 9(c)]. When the same button is depressed again to stop the activity, the maximum joint angle is recorded. The application is capable of recognizing two different activities simultaneously, one on each side of the body. A checklist of measurements is presented in between activities to indicate to the therapists which measurements have been performed [see Fig. 9(d)].

Although much effort has been invested to ensure that the activity detection algorithm identifies the correct activity, there may be instances when the subject may not be capable of adopting the right neutral posture, or when the subject is not capable of moving enough to trigger the detection. In such situations, a manual override can be invoked by tapping on the name of the activity. The user will then be presented with a list of activities to choose from.
III. DATA COLLECTION

A. Methodology

A preliminary study was conducted, where the system was tested on five subjects undergoing rehabilitation at AMKH (2 males and 3 females, mean age of 68 years). All participants were newly disabled in-patients (less than 3 months) undergoing rehabilitation for a wide variety of diagnoses. Research ethics approval was obtained from the NUS Institutional Review Board (Reference Code 11-013 and Approval Number NUS-1270). All subjects provided informed consent, and participation was voluntary. The purpose of the study was to determine the agreement between existing goniometric measurements and measurements by the system. Feedback on the usability of the system was also gathered from therapists and patients during the study.

Two therapists, each with more than ten years of experience in neuro-rehabilitation of stroke patients were recruited to perform manual measurements using goniometers. The goniometers used were from HighRes (Baseline®, ±1°), as these are the standard instruments used by the therapists. Maximal active ROM measurements were taken when the subject wearing the sensor system has achieved the maximal excursion of a particular movement in a specific joint by a therapist following protocols described by Clarkson [28]. The equivalent angle measured by the sensor was recorded by an independent engineering research assistant.

A typical assessment consists of the 12 activities listed in Table II. The activities were performed sequentially, while the order of the activities were not fixed. Each subject was subjected to two consecutive assessments on the same day, each time by a different therapist, but with minimal change in node placement between the assessments. The therapists performed the measurements independently. Only one set of measurements was taken per activity per therapist, as it was too tiring for the patient to perform repeated assessments. The correlation coefficient between the values obtained by our system and the therapists were computed to quantify the similarity between the two measurements.

The agreement between the two methods was assessed using the limits of agreement approach, which provides information on the extent of random variation between the methods [29]. The mean of the differences between each pair of measurements was computed (bias), together with the 95% upper and lower bounds of the differences (reference interval). The results are visualized using a Bland–Altman plot, as shown in Fig. 10(b). Briefly, the Bland–Altman plot illustrates the difference between each pair of measurements against the mean of the pair of measurements. The mean and reference interval are also illustrated as horizontal lines. The resulting plot depicts the overall degree of agreement, as well as how well the methods agree in relation to the magnitude of the measurement.

To evaluate the interchangeability of the two methods, the intra-class correlation coefficient (ICC) was used [30]. The ICC describes “the proportion of variance of an observation due to between-subject variability in the true scores” [30]. The index ranges from 0 to 1, with a higher index corresponding to lower variations between measurements. Each measurement was treated as an item in the ICC model, and pairs of results from both tools were treated as raters. As each angle was only measured once by both methods, the ICC(A,1) index was used [30]. In accordance to the proposal by [31], two methods can be judged interchangeable provided 1) no marked additive or non-additive systematic bias is exhibited by each method; 2) the difference between the two mean readings is not “statistically significant”; and 3) the lower limit of the 95% confidence interval of the ICC is at least 0.75.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>ACTIVITIES AND THEIR RESPECTIVE NEUTRAL POSTURES</th>
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<tbody>
<tr>
<td>Neutral 0</td>
<td>Neutral 1</td>
</tr>
<tr>
<td>Shoulder Flexion</td>
<td>Forearm Pronation</td>
</tr>
<tr>
<td>Shoulder Extension</td>
<td>Forearm Supination</td>
</tr>
<tr>
<td>Shoulder Abduction</td>
<td>Arm Internal Rotation</td>
</tr>
<tr>
<td>Elbow Flexion</td>
<td>Arm External Rotation</td>
</tr>
</tbody>
</table>

![Fig. 10. Plots comparing the system with goniometer readings. (a) System versus goniometer plot (correlation coefficients for individual activities are listed in the legend). (b) Bland–Altman plot.](image)

<table>
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<tr>
<th>TABLE III</th>
<th>ICC RESULTS FOR OVERALL INTERCHANGEABILITY</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICC</td>
<td>Lower bound</td>
</tr>
<tr>
<td>0.981</td>
<td>0.976</td>
</tr>
</tbody>
</table>
TABLE IV

| TABLE STATISTICS FOR EACH OF THE ACTIVITIES PERFORMED BY THE TWO THERAPISTS |
|---------------------------------|-----------------|-----------------|-----------------|
|                                | Therapist 1     | Therapist 2     | Difference in bias between therapists |
|                                | Bias            | LB              | UB              | Bias            | LB              | UB              | |
| Shoulder Flexion               | 5.10            | -11.40          | 21.60           | 0.20            | -16.71          | 17.11           | 4.90 |
| Shoulder Extension              | -2.60           | -8.72           | 3.52            | -2.65           | -13.37          | 8.12            | 0.05 |
| Shoulder Abduction              | 6.20            | -5.38           | 17.78           | -2.40           | -17.95          | 13.15           | 8.60 |
| Arm Internal Rotation           | -0.30           | -13.70          | 13.10           | 6.30            | -9.95           | 22.55           | 6.60 |
| Arm External Rotation           | 5.50            | -9.91           | 20.91           | 7.60            | -7.64           | 22.84           | 2.10 |
| Elbow Flexion                  | 4.33            | -12.22          | 20.89           | -0.30           | -18.34          | 17.74           | 4.63 |
| Forearm Pronation              | -10.60          | -33.68          | 12.48           | -2.40           | -21.14          | 16.34           | 8.20 |
| Forearm Supination              | 0.90            | -20.86          | 22.66           | 4.30            | -15.25          | 23.85           | 3.40 |
| Wrist Flexion                  | 0.20            | -11.34          | 11.74           | 1.80            | -11.22          | 14.82           | 1.60 |
| Wrist Extension                | 0.30            | -7.36           | 7.96            | 1.10            | -10.99          | 13.19           | 0.80 |
| Wrist Radial Deviation         | -1.00           | -10.19          | 8.19            | -0.60           | -15.33          | 14.13           | 0.40 |
| Wrist Ulnar Deviation          | -2.75           | -13.13          | 7.63            | 0.30            | -8.60           | 9.20            | 3.05 |

LB and UB denote the lower and upper bounds of the limits of agreement respectively (all values are shown in units of degrees).

B. Results

The data collected during our study are shown in Fig. 10(a). Each data point indicates a measurement that was collected simultaneously by our system and by one of the therapists. Overall, we found the correlation coefficient between the two measurements to be 0.963, with individual activities exhibiting correlation coefficients that ranged from 0.49 (for elbow flexion) to 0.91 (for shoulder extension). This showed that the measurements provided by our system were similar to those obtained by therapists, but could be obtained much more easily and quickly.

The Bland–Altman plot is shown in Fig. 10(b). We found the mean difference between the two methods to be 0.82°, suggesting that there was minimal bias between the methods. The 95% reference interval was from −15.21° to 16.84°, which represented the extent to which the methods differed. This was not unexpected as goniometry is known to have a reliability of ±10° [32].

The ICC for the two methods was computed to be 0.981, with the lower bound of the 95% confidence interval at 0.976. This demonstrates strong interchangeability, as it far exceeds the criteria of 0.75 set by Lee et al. in [31].

Breaking down the results into individual activities yielded mixed results (see Table IV). It is apparent that activities such as shoulder flexion, shoulder abduction, internal rotation of the arm, elbow flexion, and forearm pronation all exhibited significant differences in biases between the two therapists. As the nodes were not shifted between the two readings taken by the therapists, the difference in bias may be considered as a sign of intertherapist inconsistency. This is not surprising, as research has shown that in the absence of standardized measurement procedures, interrater reliability for goniometry tends to be poor [33], [34]. However, this is not enough to conclude that the proposed system is more precise, since no replicate measurements were performed for each joint angle [35]. This is because it was not possible for patients to replicate the same joint angle across assessments. In addition, there may have been some errors introduced in the system’s readings as the straps used to mount the nodes may not have been secure enough. For example, during activities such as elbow flexion or shoulder flexion, bulging of muscles or movement of clothing beneath the straps can affect the alignment of the node on the limbs. Further improvement is hence required to minimize such errors.

As therapist and system measurements were taken from the same assessments, we could not directly compare the amount of time saved from using the system. Nevertheless, time taken for each activity was logged by the system. On average, measurement of a single activity took 18 s by the therapist, while the system took only 2 s. This does not include the time needed to assist and guide the patient to perform the activities. A typical complete assessment took 54 min on average. It should be noted that the system is capable of recording from both sides simultaneously, but this feature was not exploited in our experiment. Further time savings could potentially be achieved if that were the case.

IV. Discussion

As a proof of concept, the system has demonstrated the ability of mobile platforms to perform real-time data acquisition and interpretation, in the form of measuring joint angles and detecting the type of activity. The system has also shown comparable levels of accuracy in measuring a range of joint angles when compared to the goniometer. More importantly, the time required to conduct the assessment has been dramatically reduced through the use of the system. However, to conclusively access accuracy and reproducibility of the devices, multiple sets of testing need to be done, and we are currently in the process of doing so.

Due to the continuous nature of the data acquisition, the system is able to capture additional information not easily available currently. For example, the system is able to capture transient maximum joint angles, which are maximum joint angles that a subject can achieve, but is unable to sustain. Therapists, however, can only measure sustained angles, as the subject needs to hold the angle for a period long enough for the measurement to be taken. Fig. 11 illustrates one such situation.

Feedback from the clinicians was that the transient maximum angles are important, as they represent the actual maximum range of motion of a joint. The period of time in which the subject can hold a transient maximum is also a sign of muscle

...
endurance. Other qualitative measures, such as the time-course of angular change, potentially has important applications under spasticity conditions including stroke and spinal cord injury, as well as rigidity/tremor conditions such as Parkinson’s disease. Such information would be useful in guiding measurement and therapeutic interventions.

With such a mobile platform in place, it is now possible to design assessment procedures that are more comprehensive and representative of the range of movements required by patients in a natural setting, as the entire system can be deployed anywhere and at any time. The excellent Internet connectivity of smartphones also means that a comprehensive telehabilitation system with remote assessment capabilities can be established in the near future. Further advances in MEMS fabrication would also mean that much smaller devices with minimal power consumption or energy-harvesting circuitry would improve the comfort and convenience of wearing such devices.

V. CONCLUSION

In this paper, a smartphone centric, wireless wearable system for automating joint ROM measurements has been described. A preliminary test on five patients in a clinical setting has been conducted, and the results are generally positive. In the long run, it is our aim to use the system to measure other aspects such as balance and muscle synergies, both important aspects in providing a comprehensive poststroke assessment, while remaining low-cost, portable, and easy to use. Toward that end, a larger study is required to validate the accuracy and reliability of the system on a sufficiently large group of poststroke patients.

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REFERENCES


Wang Wei Lee received the the B.Eng degree (with the First Class Hons.) in computer engineering from the Department of Electrical and Computer Engineering, National University of Singapore, in 2012, where he is currently working toward the Ph.D. degree under the supervision of Prof. N. Thakor, Dr. Y. Shih-Cheng and Dr. Y. Haoyong.

His current research interests include Neuromorphic Tactile Sensing and its applications.

Shih-Cheng Yen received the B.S.E. and M.S.E. in 1993, and the Ph.D. in 1998, all from the Department of Bioengineering, University of Pennsylvania, Philadelphia, PA, USA.

He is currently an Assistant Professor in the Department of Electrical and Computer Engineering, National University of Singapore, and also serves as the Deputy Director of the Singapore Institute of Neurotechnology (SINAPSE). His research focuses on the neural coding, neuroprostheses, and neurotherapeutic devices.

Ee Beng Arthur Tay received the B.Eng. and Ph.D. degrees in electrical engineering from the National University of Singapore, Singapore, in 1995 and 1998, respectively.

He is currently an Associate Professor with the Department of Electrical and Computer Engineering, National University of Singapore, Singapore. His research interests include applications of mathematical system science tools in biomedical engineering, semiconductor manufacturing, and process control.

Ziyi Zhao, photograph and biography not available at the time of publication.

Tim Ma Xu graduated from Nanyang Polytechnic in 2000. He completed Bachelor in Sciences (Occupational Therapy) at Curtin University of Technology, Australia, in 2005 and Master of Occupational Therapy degree from La Trobe University, Australia, in 2008.

He is currently the Operations Manager and Principal Occupational Therapist at the THK Therapy Services, Thye Hua Kwan Moral Charities.

Karen Koh Mui Ling received the Bachelor’s degree in health sciences (Physiotherapy) from The University of Sydney, Sydney, Australia, in 1999.

She is currently a Research Coordinator at the Saw Swee Hock School of Public Health, National University of Singapore. Her research interests include rehabilitation.

Yee-Sien Ng received the Bachelor of Medicine and Surgery from the National University of Singapore and completed a Fellowship in Neuro-rehabilitation from Harvard Medical School.

He is currently the Head and Senior Consultant of the Department of Rehabilitation Medicine at the Singapore General Hospital in Singapore. He is also a member of the Royal Colleges of Physicians in the U.K. His main research interests are in neurorehabilitation, spasticity, rehabilitation engineering, and the epidemiology of disability.

Effie Chew completed her medical degree at the University of Melbourne, Australia and advanced specialist training in Rehabilitation Medicine in Singapore.

She obtained her fellowship in neurorehabilitation at Spaulding Rehabilitation Hospital, Department of Physical Medicine and Rehabilitation, Harvard Medical School. She is currently a Consultant in Rehabilitation Medicine, Division of Neurology, University Medicine Cluster, National University Hospital (NUH).

Angela Lou Kuen Cheong received the Bachelor’s degree in health sciences (Nursing) from The University of Sydney, Darlington, N.S.W., Australia, in 2009.

She is currently a Research Assistant at the Saw Swee Hock School of Public Health, National University Health System, National University of Singapore. Her research interests include stroke and geriatric rehabilitation.

Gerald Koh Choon Huat received the Master’s degree in family medicine in 2000, the Master’s degree in gerontology and geriatrics from the European Institute of Gerontology, University of Malta, Msida, Malta, in 2009, and the Ph.D. degree in family medicine from Western University, Canada, in 2012.

He is currently an Associate Professor and Director of Medical Undergraduate Education at Saw Swee Hock School of Public Health. His current research interests include stroke and geriatric rehabilitation, and medical education.
A Smartphone-Centric System for the Range of Motion Assessment in Stroke Patients

Wang Wei Lee, Shih-Cheng Yen, Arthur Tay, Ziyi Zhao, Tian Ma Xu, Karen Koh Mui Ling, Yee-Sien Ng, Effie Chew, Angela Lou Kuen Cheong, and Gerald Koh Choon Huat

Abstract—The range of motion (ROM) in stroke patients is often severely affected. Poststroke rehabilitation is guided through the use of clinical assessment scales for the rROM. Unfortunately, these scales are not widely utilized in clinical practice as they are excessively time-consuming. Although commercial motion-capture systems are capable of providing the information required for the assessments, most systems are either too costly or lack the convenience required for assessments to be conducted on a daily basis. This paper presents the design and implementation of a smartphone-based system for automated motion assessment using low-cost off-the-shelf inertial sensors. The system was used to automate a portion of the upper-extremity Fugl–Meyer assessment (FMA), which is widely used to quantify motor deficits in stroke survivors. Twelve out of 33 items were selected, focusing mainly on joint angle measurements of the upper body. The system has the ability to automatically identify the assessment item being conducted, and calculate the maximum respective joint angle achieved. Preliminary results show the ability of this system to achieve comparable results to goniometer measurements, while significantly reducing the time required to conduct the assessments. The portability and ease-of-use of the system would simplify the task of conducting range-of-motion assessments.

Index Terms—Body sensor networks, mobile nodes, patient rehabilitation, wearable sensors.

I. BACKGROUND

STROKE is the fourth leading cause of death in the United States, with about 795,000 people experiencing stroke each year [1]. Globally, an estimated 15 million people suffer stroke yearly [2]. In Singapore, stroke is a major cause of death, with more than 10,000 new patients being hospitalized due to stroke each year [3]. Stroke affects a person’s cognitive, language, perceptual, sensory, and motor abilities [4]. The recovery process is very long, extending beyond the hospital stay and into the home setting, and are guided by clinical assessments such as their range of motion. Accurate assessment of their ranges is hence crucial in selecting the best therapies for stroke patients.

The Fugl–Meyer assessment of sensorimotor recovery after stroke (FMA) is widely used in clinical trials to quantify motor deficits in patients after stroke [5]. The main evaluation aspects of the FMA include motor movements, balance, sensation, joint ROM and pain, thus providing a concise scale to quantify stroke severity with sound psychometric properties. However, the FMA is rarely used in clinics due to its lengthy administration time, as it consists of a 33-item upper extremity subscale and a 17-item lower extremity subscale [6]. A typical full-scale assessment would require more than an hour to conduct. A shorter version of the FMA (S-FM) was developed by Hsieh et al. [7] to reduce its administration time. Despite the reduction in items, the S-FM is still not very widely used. One of the reasons is that the S-FM is still based on observations of subjects’ motor behavior, and measurements are conducted manually using a goniometer or visual estimation. As a result, the accuracy and consistency may vary greatly across clinicians [8]. A precise, reliable, yet convenient method of performing such assessments is thus imperative, and this is where the use of electronic tools may be useful.

The first step to such an effective electronic assessment tool is the ability to accurately measure joint ROM. Traditionally, electronic assessments of ROM are performed using multicamera vision systems, which are often too elaborate, expensive, and inconvenient to perform on large numbers of patients. Other vision-based systems such as Microsoft Kinect have seen significant adoption in applications for posture and gesture detection. However, such systems suffer from skeletal merging [9] and thus do not work reliably when the caregiver is within the field of view of the camera, or if the subject were to sit on a wheelchair/bed. In recent years, there have been a growing number of attempts to track movements in humans using wearable devices instead [10]. Methods such as e-textiles [11], optical linear encoders [12], and fiber optics [13] have been investigated with the aim of providing accurate joint angle measurements. However, these approaches require the calibration of equipment for individual patients, due to the variations in joint sizes and skin elasticity. Inertial measurement units (IMU) are less sensitive to such variations, since they work by comparing orientation between limbs, instead of measuring the amount
of bend at a joint. In IMU systems, MEMS (microelectromechanical systems) sensors such as accelerometers, gyroscopes, magnetometers or a combination of them are used to estimate the orientation of the limbs the sensors are attached to. Estimation of joint angles and joint kinematics using IMUs have been extensively studied [14]–[18]. The accuracy and reliability of IMU-based systems have since improved to the point where applications in motion capture, gait, and posture analysis are also possible [19], [20], and commercial motion capture systems are now readily available [21], [22].

Despite the availability of technology for accurate joint motion capture, a convenient, user-friendly and cost-effective motor ability assessment tool has yet to appear. Many of the systems mentioned are rather complicated, requiring skilled personnel to operate. In addition, these systems often require a PC to process the data from the sensors, which translates to reduced portability and convenience.

The aim of this paper is to introduce a new joint-angle measurement system, designed specifically for physicians to conduct ROM assessments quickly and easily within the hospital. Although it is also based on IMUs, the system is operated from a smartphone instead, thus improving its mobility. As a start, 12 simple assessment activities from the upper extremity FMA that do not involve muscle-group synergies were selected and implemented in the system. These activities can be automatically identified and measured by the system, thus ensuring that the interface remains simple and user friendly. Developed in collaboration with healthcare professionals from Singapore General Hospital (SGH) and Ang Moh Kio-Thye Hwa Kwan community Hospital (AMKH), the system aims to provide doctors and therapists with a practical tool to perform ROM measurements.

Section II will elaborate on the design and implementation considerations of the system. Section III focuses on validating the accuracy of the system against the goniometer, while Sections IV and V present the discussion and conclusions, respectively.

II. DESIGN AND DEVELOPMENT

A. System Architecture

There are two main parts to the system (see Fig. 1)—the sensor nodes (see Fig. 2) and the application. The sensor nodes are responsible for acquiring data on the orientation and movement of the patient’s limbs. A total of seven sensor nodes are used. Each node includes tri-axial accelerometer, gyroscope, and magnetometer sensors that are polled by an on-board microcontroller. Also included is a wireless communication module and battery. Each node measures 66.6 mm × 28.2 mm × 18.1 mm and weighs 22 g. When used with a fully charged battery, each node lasts 179 min on average.

A sensor-fusion algorithm runs on each node, where raw sensor readings are combined to continuously update the 3-D orientation of the sensor. Compared to implementing the fusion algorithm on the smartphone, calculations performed on individual nodes greatly reduce the computational load on the smartphone, while improving reliability of the orientation estimates since it does not have to deal with the possible loss of sensor readings during wireless transmission.

The IEEE 802.15.4 [23] standard for wireless communication is used for all nodes, in order to reduce size and power consumption. A single larger node capable of communicating on both WiFi and the IEEE 802.15.4 standard is included in the system. Known as the master node, it acts as a bridge between the other (slave) nodes and the smartphone, while at the same time collecting data from its on-board sensors. This eliminates the need for a separate network adapter for the phone. Another advantage of this solution is the distribution of processing load, as the master node encapsulates the network protocol needed to communicate with the rest of the slave nodes. The architecture of the sensor layer is illustrated in Fig. 3.

The application layer runs on an Android smartphone. It receives the orientation of all nodes from the master node via WiFi, from which the posture of the subject can then be derived. The computation of joint angles and the identification of assessment exercises are performed at this stage. The application also serves as the user interface of the system.

B. System Configuration

The system is built using commercially available components. Each slave node consists of an 8 bit microprocessor (ATMEGA328, Atmel), a triaxial accelerometer (ADXL345, Analog Devices), a triaxial gyroscope (ITG3200, InvenSense), a triaxial magnetometer (HMC5883L, Honeywell), as well as a IEEE 802.15.4 compliant wireless module (XB24-A, Digi). The master node uses a different microprocessor (LPC1768, NXP), and also includes a WiFi module (RN-131C, Roving Networks) in addition to the sensors used on the slave nodes.
Fig. 3. Sensor-layer architecture in detail.

Fig. 4. Placement of nodes on a patient. (a) Back. (b) Upper Arm. (c) Lower Arm. (d) Wrist.

Fig. 5. Pipelined data transmission.

MSM7227) and 384 MB of RAM, both of which operate on version 2.2 (Froyo) of the Android operating system.

The system is configured to sample at 25 Hz, which is more than sufficient to capture a stroke patient’s motion activities because of the degraded motor function. 25 Hz is also sufficient for detecting abnormal tremors [24], although this feature was not yet implemented. The sampling rate was limited by the wireless bandwidth (IEEE:802.15.4) available.

C. Communication

A star network topology is adopted for internodal wireless communication, where the master node maintains a direct communication link to the slave nodes.

In order to minimize data loss due to wireless packet collisions, time divisional multiple access (TDMA) is implemented by an application layer protocol (See Fig. 5). Under this scheme, beacon signals are broadcast by the master node to demarcate the boundaries of each period. Each period consists of multiple time slots reserved for slave nodes to transmit data. Hardware timer and serial interrupts are used to ensure that all slave nodes adhere to strict timing constraints, transmitting only within their predefined time slots. With this implementation in place, the system has been tested to be capable of interfacing up to seven slave nodes at 25 Hz, with minimal data loss from packet collision. This was later verified using time stamps on samples from experiments performed on patients. An average of 3.5% of packets were lost per session, while the average time between consecutive samples was 40 ms.

D. Orientation Sensing

Data fusion of the readings from the accelerometer, gyroscope, and magnetometer provides consistent orientation estimates while reducing gyroscope drift, as well as measurement noise from the accelerometer and magnetometer [25]. While many commercial orientation sensors adopt the Kalman filter due to its accuracy and effectiveness [26], they can be
Central to the system is the user interface. A sensor node was strapped onto the subject, and the orientation of the sensor. Not only is it a more compact representation compared to discrete cosine matrices, it also avoids the problem of gimbal lock when the pitch reaches ±90° (as compared to Euler Angles) [27].

The system uses quaternions [27] to describe the estimated orientation of the sensor. Not only is it a more compact representation compared to discrete cosine matrices, it also avoids the problem of gimbal lock when the pitch reaches ±90° (as compared to Euler Angles) [27].

To relate the sensor frame to Earth frame of reference for comparison, vectors representing the x-, y-, and z-axis components in the sensor frame were multiplied by the discrete cosine matrix (DCM) derived from the quaternion output of the algorithm. Equation (1) describes the formula to obtain the DCM for converting from sensor frame to Earth frame, where q0 to q3 are elements of the quaternion:

\[
\text{DCM} = \begin{bmatrix}
2q_0^2 - 1 + 2q_1^2 & 2(q_1q_2 - q_0q_3) & 2(q_1q_3 + q_0q_2) \\
2(q_1q_2 + q_0q_3) & 2q_0^2 - 1 + 2q_2^2 & 2(q_2q_3 - q_0q_1) \\
2(q_1q_3 - q_0q_2) & 2(q_2q_3 + q_0q_1) & 2q_0^2 - 1 + 2q_3^2
\end{bmatrix}
\]

To evaluate the accuracy of the system, the sensor-fusion algorithm was tested against a 10 camera Vicon Bonita optical system (accuracy ± 0.5 mm). A sensor node was strapped onto the Active Wand provided by the manufacturer, which is a rigid structure with optical markers meant for calibration [See Fig. 6(a)]. The sampling rate of the optical system was set to 200 Hz, while signal acquisition and computation of angles was performed using Vicon Tracker software version 1.3.1. The quaternion output from the sensor node was computed at 25 Hz and conversion to angles was performed offline. For comparison, the output from the Vicon system was downsampled to match the system output.

Before each test, the wand was left stationary for 10 s for the algorithm to converge. This initial position was also used to offset between the optical system’s coordinate frame and Earth frame as computed by the sensor. The wand was then offset along the x-axis of the Earth frame, followed by another offset on the x-axis in the opposite direction, beyond the initial position. Such movements were repeated at least 15 times for each axis with offset magnitudes within ±90°. The maximum angular velocity during movement was always below 360°/s. All movements were conducted by hand.

The root-mean-squared error was computed on the difference between the two systems, and results were tabulated in Table I. The error was found to be within 5° in all the three planes of interest. This was higher than the error reported in [25], possibly due to the much lower sampling rate used (25 Hz versus 512 Hz) as well as magnetic interference from the circuitry within the Active Wand. Nevertheless, this performance should be sufficient for our application.

E. User Interface

1) Design Criteria: Central to the system is the user interface (UI), and one important requirement is its usability. Therapists often have to pay full attention to guiding and supporting their patients during the assessments, and thus cannot afford to spend much time setting up and operating a system.

Another requirement mentioned is the flexibility of the software during operation. The therapist should not be forced to conduct the assessment exercises in a predefined order, as depending on the current posture of the patient, the therapist may want to start with the most convenient assessment exercise first.

Taking the above factors into account, the system adopts a very minimalist UI. Only crucial information is displayed on the screen, and large fonts are used to render them. In most cases, only one button is needed to conduct the full assessment. Audio cues are used to indicate to the therapist when a measurement is obtained, thus reducing the need to constantly look at the smartphone during the assessment.

2) Automatic Exercise Detection: One innovative feature of the UI is an activity detection algorithm. This feature eliminates the need for the user to scroll through a long list to select different exercises, while still allowing the user to conduct the assessment in any order.

The algorithm works by comparing the initial and final orientation of the limbs. While most exercises (e.g., shoulder flexion, extension, abduction) involve the measurement of an angle with respect to a fixed reference (e.g., gravity vector), some exercises, such as wrist ulnar deviation, involve the measurement of the angle between the starting and ending positions. As such, there is a need to manually indicate to the system when the subject has adopted the starting position. A system of neutral postures was thus introduced. Neutral postures are postures that a subject must adopt at the beginning of each assessment exercise. The orientation of the sensors in each neutral posture corresponds to the starting position for the exercise, thus providing a reference from which the end position will be measured against (See Fig. 7). Note that Neutral 0 is optional as the computation of joint ROM for each of the activities do not require the initial
angle to be known. However, adopting Neutral 0 at the beginning of an activity would still improve detection accuracy, as the number of possible activities would be reduced. Note that the neutral positions adopted here are not the ones that are commonly used in the FMA [5], [7]. These neutral positions were adopted primarily to make it easier for us to measure the range of motion of different joints.

The logic used in activity detection is based on a set of experimentally derived thresholds, and guided by the patient’s posture at the start of the activity. Fig. 8 illustrates the logic flow. For example, a patient starting in neutral posture 2 who flexes his/her wrist downward would be recognized as performing the wrist-flexion assessment.

The algorithm has been kept intentionally simple considering the limited processing capability of mobile phones, although the accuracy should improve with further refinement and better hardware.

3) Operation: The smartphone has to enable WiFi hotspot mode to connect to the master node. The master node searches for the pre-defined SSID of the hotspot when turned on. To establish the connection, the user has to press the Connect button after the application is launched [See Fig. 9(a)].

Before the assessment begins, the user has to enter the identification of the patient. The user is then taken to the assessment interface once the ID is entered. Within the assessment interface, there is only a single toggle button to start and stop the activity. The subject should adopt the respective neutral posture before the start button is pressed. Automatic activity detection begins once the start button is pressed. Once the application recognizes the activity, a ‘beep’ sound is played, while it continuously calculates the respective joint angle [see Fig. 9(c)]. When the same button is depressed again to stop the activity, the maximum joint angle is recorded. The application is capable of recognizing two different activities simultaneously, one on each side of the body. A checklist of measurements is presented in between activities to indicate to the therapists which measurements have been performed [see Fig. 9(d)]. Although much effort has been invested to ensure that the activity detection algorithm identifies the correct activity, there may be instances when the subject may not be capable of adopting the right neutral posture, or when the subject is not capable of moving enough to trigger the detection. In such situations, a manual override can be invoked by tapping on the name of the activity. The user will then be presented with a list of activities to choose from.
TABLE II
ACTIVITIES AND THEIR RESPECTIVE NEUTRAL POSTURES

<table>
<thead>
<tr>
<th>Neutral 0</th>
<th>Neutral 1</th>
<th>Neutral 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shoulder Flexion</td>
<td>Forearm Pronation</td>
<td>Wrist Flexion</td>
</tr>
<tr>
<td>Shoulder Extension</td>
<td>Forearm Supination</td>
<td>Wrist Extension</td>
</tr>
<tr>
<td>Shoulder Abduction</td>
<td>Arm Internal Rotation</td>
<td>Wrist Radial Deviation</td>
</tr>
<tr>
<td>Elbow Flexion</td>
<td>Arm External Rotation</td>
<td>Wrist Ulnar Deviation</td>
</tr>
</tbody>
</table>

III. DATA COLLECTION

A. Methodology

A preliminary study was conducted, where the system was tested on five subjects undergoing rehabilitation at AMKH (2 males and 3 females, mean age of 68 years). All participants were newly disabled in-patients (less than 3 months) undergoing rehabilitation for a wide variety of diagnoses. Research ethics approval was obtained from the NUS Institutional Review Board (Reference Code 11-013 and Approval Number NUS-1270). All subjects provided informed consent, and participation was voluntary. The purpose of the study was to determine the agreement between existing goniometric measurements and measurements by the system. Feedback on the usability of the system was also gathered from therapists and patients during the study.

Two therapists, each with more than ten years of experience in neuro-rehabilitation of stroke patients were recruited to perform manual measurements using goniometers. The goniometers used were from HighRes (Baseline©, ±1°), as these are the standard instruments used by the therapists. Maximal active ROM measurements were taken when the subject wearing the sensor system has achieved the maximal excursion of a particular movement in a specific joint by a therapist following protocols described by Clarkson [28]. The equivalent angle measured by the sensor was recorded by an independent engineering research assistant.

A typical assessment consists of the 12 activities listed in Table II. The activities were performed sequentially, while the order of the activities were not fixed. Each subject was subjected to two consecutive assessments on the same day, each time by a different therapist, but with minimal change in node placement between the assessments. The therapists performed the measurements independently. Only one set of measurements was taken per activity per therapist, as it was too tiring for the patient to perform repeated assessments. The correlation coefficient between the values obtained by our system and the therapists were computed to quantify the similarity between the two measurements.

The agreement between the two methods was assessed using the limits of agreement approach, which provides information on the extent of random variation between the methods [29]. The mean of the differences between each pair of measurements was computed (bias), together with the 95% upper and lower bounds of the differences (reference interval). The results are visualized using a Bland–Altman plot, as shown in Fig. 10(b). Briefly, the Bland–Altman plot illustrates the difference between each pair of measurements against the mean of the pair of measurements. The mean and reference interval are also illustrated as horizontal lines. The resulting plot depicts the overall degree of agreement, as well as how well the methods agree in relation to the magnitude of the measurement.

To evaluate the interchangeability of the two methods, the intra-class correlation coefficient (ICC) was used [30]. The ICC describes “the proportion of variance of an observation due to between-subject variability in the true scores” [30]. The index ranges from 0 to 1, with a higher index corresponding to lower variations between measurements. Each measurement was treated as an item in the ICC model, and pairs of results from both tools were treated as raters. As each angle was only measured once by both methods, the ICC(A,1) index was used [30]. In accordance to the proposal by [31], two methods can be judged interchangeable provided 1) no marked additive or non-additive systematic bias is exhibited by each method; 2) the difference between the two mean readings is not “statistically significant”; and 3) the lower limit of the 95% confidence interval of the ICC is at least 0.75.

TABLE III
ICC RESULTS FOR OVERALL INTERCHANGEABILITY

<table>
<thead>
<tr>
<th>ICC</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.981</td>
<td>0.976</td>
<td>0.985</td>
</tr>
</tbody>
</table>
TABLE IV
BA PLOT STATISTICS FOR EACH OF THE ACTIVITIES PERFORMED BY THE TWO THERAPISTS

<table>
<thead>
<tr>
<th>Activity</th>
<th>Therapist 1</th>
<th>Therapist 2</th>
<th>Difference in bias between therapists</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bias</td>
<td>LB</td>
<td>UB</td>
</tr>
<tr>
<td>Shoulder Flexion</td>
<td>5.10</td>
<td>-11.40</td>
<td>21.60</td>
</tr>
<tr>
<td>Shoulder Extension</td>
<td>-2.60</td>
<td>-8.72</td>
<td>3.52</td>
</tr>
<tr>
<td>Shoulder Abduction</td>
<td>6.20</td>
<td>-5.38</td>
<td>17.78</td>
</tr>
<tr>
<td>Arm Internal Rotation</td>
<td>-0.30</td>
<td>-13.70</td>
<td>13.10</td>
</tr>
<tr>
<td>Arm External Rotation</td>
<td>5.50</td>
<td>-9.91</td>
<td>20.91</td>
</tr>
<tr>
<td>Elbow Flexion</td>
<td>4.33</td>
<td>-12.22</td>
<td>20.89</td>
</tr>
<tr>
<td>Forearm Pronation</td>
<td>-10.60</td>
<td>-33.68</td>
<td>12.48</td>
</tr>
<tr>
<td>Forearm Supination</td>
<td>0.90</td>
<td>-20.86</td>
<td>22.66</td>
</tr>
<tr>
<td>Wrist Flexion</td>
<td>0.20</td>
<td>-11.34</td>
<td>11.74</td>
</tr>
<tr>
<td>Wrist Extension</td>
<td>0.30</td>
<td>-7.36</td>
<td>7.96</td>
</tr>
<tr>
<td>Wrist Radial Deviation</td>
<td>-1.00</td>
<td>-10.19</td>
<td>8.19</td>
</tr>
<tr>
<td>Wrist Ulnar Deviation</td>
<td>-2.75</td>
<td>-13.13</td>
<td>7.63</td>
</tr>
</tbody>
</table>

LB and UB denote the lower and upper bounds of the limits of agreement respectively (all values are shown in units of degrees).

B. Results

The data collected during our study are shown in Fig. 10(a). Each data point indicates a measurement that was collected simultaneously by our system and by one of the therapists. Overall, we found the correlation coefficient between the two measurements to be 0.963, with individual activities exhibiting correlation coefficients that ranged from 0.49 (for elbow flexion) to 0.91 (for shoulder extension). This showed that the measurements provided by our system were similar to those obtained by therapists, but could be obtained much more easily and quickly.

The Bland–Altman plot is shown in Fig. 10(b). We found the mean difference between the two methods to be 0.82°, suggesting that there was minimal bias between the methods. The 95% reference interval was from $-15.21^\circ$ to $16.84^\circ$, which represented the extent to which the methods differed. This was not unexpected as goniometry is known to have a reliability of $\pm10^\circ$ [32].

The ICC for the two methods was computed to be 0.981, with the lower bound of the 95% confidence interval at 0.976. This demonstrates strong interchangeability, as it far exceeds the criteria of 0.75 set by Lee et al. in [31].

Breaking down the results into individual activities yielded mixed results (see Table IV). It is apparent that activities such as shoulder flexion, shoulder abduction, internal rotation of the arm, elbow flexion, and forearm pronation all exhibited significant differences in biases between the two therapists. As the nodes were not shifted between the two readings taken by the therapists, the difference in bias may be considered as a sign of intertherapist inconsistency. This is not surprising, as research has shown that in the absence of standardized measurement procedures, interrater reliability for goniometry tends to be poor [33], [34]. However, this is not enough to conclude that the proposed system is more precise, since no replicate measurements were performed for each joint angle [35].

For example, during activities such as elbow flexion or shoulder flexion, bulging of muscles or movement of clothing beneath the straps can affect the alignment of the node on the limbs. Further improvement is hence required to minimize such errors.

As therapist and system measurements were taken from the same assessments, we could not directly compare the amount of time saved from using the system. Nevertheless, time taken for each activity was logged by the system. On average, measurement of a single activity took 18 s by the therapist, while the system took only 2 s. This does not include the time needed to assist and guide the patient to perform the activities. A typical complete assessment took 54 min on average. It should be noted that the system is capable of recording from both sides simultaneously, but this feature was not exploited in our experiment. Further time savings could potentially be achieved if that were the case.

IV. Discussion

As a proof of concept, the system has demonstrated the ability of mobile platforms to perform real-time data acquisition and interpretation, in the form of measuring joint angles and detecting the type of activity. The system has also shown comparable levels of accuracy in measuring a range of joint angles when compared to the goniometer. More importantly, the time required to conduct the assessment has been dramatically reduced through the use of the system. However, to conclusively access accuracy and reproducibility of the devices, multiple sets of testing need to be done, and we are currently in the process of doing so.

Due to the continuous nature of the data acquisition, the system is able to capture additional information not easily available currently. For example, the system is able to capture transient maximum joint angles, which are maximum joint angles that a subject can achieve, but is unable to sustain. Therapists, however, can only measure sustained angles, as the subject needs to hold the angle for a period long enough for the measurement to be taken. Fig. 11 illustrates one such situation.

Feedback from the clinicians was that the transient maximum angles are important, as they represent the actual maximum range of motion of a joint. The period of time in which the subject can hold a transient maximum is also a sign of muscle
endurance. Other qualitative measures, such as the time-course of angular change, potentially have important applications under spasticity conditions including stroke and spinal cord injury, as well as rigidity/tremor conditions such as Parkinson’s disease. Such information would be useful in guiding measurement and therapeutic interventions.

With such a mobile platform in place, it is now possible to design assessment procedures that are more comprehensive and representative of the range of movements required by patients in a natural setting, as the entire system can be deployed anywhere and at any time. The excellent Internet connectivity of smartphones also means that a comprehensive telerehabilitation where and at any time. The excellent Internet connectivity of smartphones also means that a comprehensive telerehabilitation system with remote assessment capabilities can be established in the near future. Further advances in MEMS fabrication would also mean that much smaller devices with minimal power consumption or energy-harvesting circuitry would improve the comfort and convenience of wearing such devices.

V. CONCLUSION

In this paper, a smartphone centric, wireless wearable system for automating joint ROM measurements has been described. A preliminary test on five patients in a clinical setting has been conducted, and the results are generally positive. In the long run, it is our aim to use the system to measure other aspects such as balance and muscle synergies, both important aspects in providing a comprehensive poststroke assessment, while remaining low-cost, portable, and easy to use. Toward that end, a larger study is required to validate the accuracy and reliability of the system on a sufficiently large group of poststroke patients.

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Fig. 11. Transient maximum versus sustained maximum.


Wang Wei Lee received the B.Eng degree (with the First Class Hons) in computer engineering from the Department of Electrical and Computer Engineering, National University of Singapore, in 2012. He is currently working toward the Ph.D. degree under the supervision of Prof. N. Thakor, Dr. Y. Shih-Cheng, and Dr. Y. Haoyong. His current research interests include Neuromorphic Tactile Sensing and its applications.

Shih-Cheng Yen received the B.S.E. and M.S.E. in 1993, and the Ph.D. in 1998, all from the Department of Bioengineering, University of Pennsylvania, Philadelphia, PA, USA. He is currently an Assistant Professor in the Department of Electrical and Computer Engineering, National University of Singapore, and also serves as the Deputy Director of the Singapore Institute of Neurotechnology (SINAPSE). His research focuses on the neural coding, neuroprostheses, and neurotherapeutic devices.

Ee Beng Arthur Tay received the B.Eng. and Ph.D. degrees in electrical engineering from the National University of Singapore, Singapore, in 1995 and 1998, respectively. He is currently an Associate Professor with the Department of Electrical and Computer Engineering, National University of Singapore, Singapore. His research interests include applications of mathematical system science tools in biomedical engineering, semiconductor manufacturing, and process control.

Ziyi Zhao, photograph and biography not available at the time of publication.

Tim Ma Xu graduated from Nanyang Polytechnic in 2000. He completed Bachelor in Sciences (Occupational Therapy) at Curtin University of Technology, Australia, in 2005 and Master of Occupational Therapy degree from La Trobe University, Australia, in 2008. He is currently the Operations Manager and Principal Occupational Therapist at the THK Therapy Services, Thye Hua Kwan Moral Charities.

Karen Koh Mui Ling received the Bachelor’s degree in health sciences (Physiotherapy) from The University of Sydney, Sydney, Australia, in 1999. She is currently a Research Coordinator at the Saw Swee Hock School of Public Health, National University of Singapore. Her research interests include rehabilitation.

Yee-Sien Ng received the Bachelor of Medicine and Surgery from the National University of Singapore and completed a Fellowship in Neuro-rehabilitation from Harvard Medical School. He is currently the Head and Senior Consultant of the Department of Rehabilitation Medicine at the Singapore General Hospital in Singapore. He is also a member of the Royal Colleges of Physicians in the U.K. His main research interests are in neurorehabilitation, spasticity, rehabilitation engineering, and the epidemiology of disability.

Effie Chew completed her medical degree at the University of Melbourne, Australia and advanced specialist training in Rehabilitation Medicine in Singapore. She obtained her fellowship in neurorehabilitation at Spaulding Rehabilitation Hospital, Department of Physical Medicine and Rehabilitation, Harvard Medical School. She is currently a Consultant in Rehabilitation Medicine, Division of Neurology, University Medicine Cluster, National University Hospital (NUH).

Angela Lou Kuen Cheong received the Bachelor’s degree in health sciences (Nursing) from The University of Sydney, Darlington, N.S.W., Australia, in 2009. She is currently a Research Assistant at the Saw Swee Hock School of Public Health, National University Health System, National University of Singapore. Her research interests include stroke and geriatric rehabilitation.

Gerald Koh Choon Huat received the Master’s degree in family medicine in 2000, the Master’s degree in gerontology and geriatrics from the European Institute of Gerontology, University of Malta, Msida, Malta, in 2009, and the Ph.D. degree in family medicine from Western University, Canada, in 2012. He is currently an Associate Professor and Director of Medical Undergraduate Education at Saw Swee Hock School of Public Health. His current research interests include stroke and geriatric rehabilitation, and medical education.