Data Glove Embedded with 9-Axis IMU and Force Sensing Sensors for Evaluation of Hand Function

Pei-Chi Hsiao, Shu-Yu Yang, Bor-Shing Lin, I-Jung Lee and Willy Chou

Abstract—**A hand injury can greatly affect a person's daily life. Physicians must evaluate the state of recovery of a patient's injured hand. However, current manual evaluations of hand functions are imprecise and inconvenient. In this paper, a data glove embedded with 9-axis inertial sensors and force sensitive resistors is proposed. The proposed data glove system enables hand movement to be tracked in real-time. In addition, the system can be used to obtain useful parameters for physicians, is an efficient tool for evaluating the hand function of patients, and can improve the quality of hand rehabilitation.**

I. INTRODUCTION

Patients who experience hand function loss must undergo regular hand rehabilitation, during which hand function and restoration is evaluated using hand function evaluation tools. However, traditional methods, such as using a goniometer, for measuring hand function are too inaccurate and subjective and cannot yield quantitative data for evaluating hand function during rehabilitation.

Among the evaluation tools used during hand rehabilitation, data gloves are the most effective for tracking a patient's hand motion; when the patient wears the glove while performing tasks required during rehabilitation, the glove provides kinematic information of the hand that physicians can use to evaluate hand function more accurately and effectively. However, current data-glove-based evaluation systems for hand function are uncomfortable and unadaptable for every hand size, and unable to provide an adequate amount of parameters for physicians.

Data-glove-based hand function evaluation systems examined in previous studies can be classified into the following four categories: 1) mechanism architecture; 2) fiber optic sensors; 3) resistive flex sensors; and 4) inertial measurement units (IMUs). The advantages and disadvantages of each system are discussed as follows.

The earliest design of these data-glove-based systems for tracking hand motion with sensors was a mechanical architecture [1]–[2], which was used as recently as 2014 by Park [2], who proposed a data-glove-based system featuring a wire-driven mechanism for measuring the finger bending angles precisely. The advantage of this design is that it could easily and accurately assess the bending angles of every finger movement when worn on a hand during rehabilitation. However, this glove was heavy, expensive, and uncomfortable. Therefore, flexible and lighter designs incorporating optical fiber sensors have been developed [3]–[6]. The most representative data-glove-based system with optical fiber sensors, named the 5DT glove, was proposed by Cheng, *et al.* [4]. They used five groups of fiber optic sensors for measuring the finger flexure and reflecting the degree of task completeness. The lightweight and compact design resolved the problems inherent in the mechanism architecture. However, the optical fiber sensors were expensive and imprecise. In most data gloves used for rehabilitation, the primary sensors are resistive flex sensors. In 2007, Simone *et al.* proposed a data-glove-based rehabilitation system featuring resistive flex sensors [7]. This study was the most comprehensive investigation of using resistive flex sensors in a data-glove-based system for rehabilitation. The complete experiment protocol was used in later studies [8]. From 2009 to 2013, numerous data-glove-based systems incorporating resistive flex sensors were also proposed for rehabilitation [9]–[18]. The values obtained from the resistive flex sensors were used to determine the flexion of the knuckles. The advantages of this design were that the resistive flex sensors could be easily handled, were inexpensive, and could detect slight changes in finger bending angles. However, the disadvantages were that the calibration time was long because the analog signal was converted to a digital signal, and the sensors were easily worn down. The three aforementioned types of data-glove-based systems could only measure the changes in the knuckles and could not obtain detailed parameters, such as acceleration, velocity, and bending angles of knuckles, when the wearer was conducting the rehabilitation tasks. Therefore, data-glove-based systems incorporating IMUs were proposed to aid physicians in evaluating the hand functions of patients easily. In 2014, Henk *et al.* proposed the most comprehensive IMU data-glove-based system in all related studies [19]. They proposed an algorithm for measuring the fingers' knuckles accurately. However, this system was not evaluated in a clinical experiment and could not evaluate the hand function of patients or be adjusted to fit various hand sizes.

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To resolve the aforementioned problems, a data-glove-based system embedded with 9-axis IMU and force sensitive resistors is proposed for evaluating hand function.

II. METHOD

The proposed system comprises a data glove and a Windows program. Fig. 1 illustrates the system architecture. The microcontroller unit (MCU) on the main board retrieves the data from each 9-axis inertial sensor and the voltage from the force sensitive resistor on each finger. After receiving the data from the data glove, the MCU processes the raw data, encapsulates them into a packet, and sends the packet to the personal computer (PC) through a Bluetooth interface. The Windows program on the PC calculates the velocity, angle of flexion and extension, pressure, and time by using raw data collected from the accelerometer, gyroscope, magnetometer, and output voltages of the force sensitive resistors; thus, physicians can evaluate the hand function of patients.

A. Hardware Design

The hardware of this data-glove-based system comprises a glove module and a main board (Fig. 2). The main board consists of an MCU (MSP430, Texas Instruments Incorporated, Dallas, Texas, USA), the core of the proposed system, and a 9-axis IMU sensor. A 3.7 V, 600 mAh battery provides power to the system. The sampling rate of the MCU was set to 50 Hz for retrieving data from each sensor. The data retrieved from the 9-axis IMU sensor on the main board are used to measure the wrist's movement. The data are encapsulated into packets and sent to the PC through the Bluetooth interface at 200 kbps.

The proposed data-glove-based system contains seventeen 9-axis IMU sensors (LSM9DS0, ST Microelectronics, Geneva, Switzerland) and five force sensitive resistors (FSR400, Interlink Electronics, USA). Each 9-axis IMU sensor includes a 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer that output acceleration, angular velocity, and magnetic field, respectively. Three of the seventeen IMU sensors placed on the back of the hand can measure the five metacarpophalangeal joints (MCPs) accurately. The force sensitive resistors are attached to the fingertips to measure the pressure when the patient picks up objects.

Fig. 3 illustrates the design of the changeable flexible printed circuit (FPC) of the fingers. Different combinations of finger FPCs were used to adapt to various hand sizes and achieve a flexible design, the main feature of the proposed system.

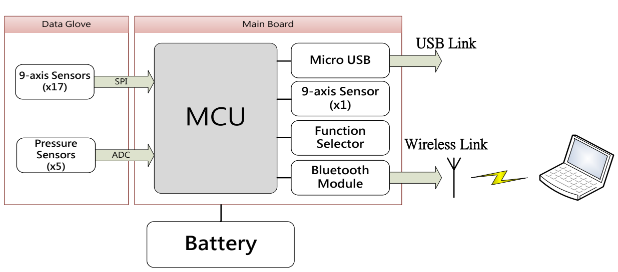

Fig. 1. Overall system architecture.

Fig. 2. Hardware of the proposed system.

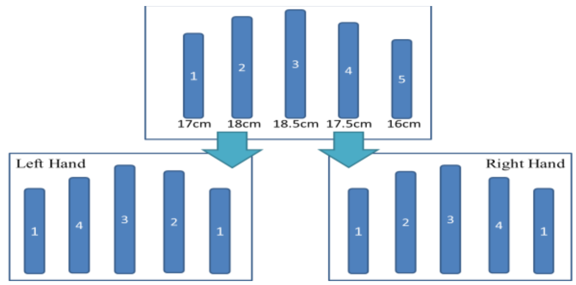

Fig. 3. Adaptive design of the FPC on the fingers.

B. Software Design

1) Quaternion-based Kalman Filter

The quaternion-based Kalman filter [20] proposed by Comotti and Ermidoro was used as the attitude estimation algorithm in this study. In this algorithm, quaternion is used as the state in every predicting and updating period.

Quaternion variation is intergraded over the sampling period δ_t. The prediction step is shown in (1), where $\vec{q}_{t-1}$ is the previous state, and $\vec{q}_t$ is the current state. Matrix $\boldsymbol{F}$ is the state transition model, expressed in (2).

$$\vec{q}_t = \vec{q}_{t-1} + \dot{q}_t \cdot \delta_t = \mathrm{F} \cdot \vec{q}_{t-1} \tag{1}$$

$$\mathrm{F} = \begin{bmatrix} 1 & -\frac{1}{2}\cdot\omega_x\cdot\delta_t & -\frac{1}{2}\cdot\omega_y\cdot\delta_t & -\frac{1}{2}\cdot\omega_z\cdot\delta_t \\ \frac{1}{2}\cdot\omega_x\cdot\delta_t & 1 & \frac{1}{2}\cdot\omega_z\cdot\delta_t & -\frac{1}{2}\cdot\omega_y\cdot\delta_t \\ \frac{1}{2}\cdot\omega_y\cdot\delta_t & -\frac{1}{2}\cdot\omega_z\cdot\delta_t & 1 & \frac{1}{2}\cdot\omega_x\cdot\delta_t \\ \frac{1}{2}\cdot\omega_z\cdot\delta_t & \frac{1}{2}\cdot\omega_y\cdot\delta_t & -\frac{1}{2}\cdot\omega_x\cdot\delta_t & 1 \end{bmatrix} \tag{2}$$

The prediction equation is expressed in (3).

$$\vec{q}_{t|t-1} = \mathrm{F} \cdot \vec{q}_{t-1|t-1}, \tag{3}$$

where $\vec{q}_{t|t-1}$ is the prediction vector, and $\vec{q}_{t-1|t-1}$ is the output of the filter at the previous step.

The step of updating the predicted state $\vec{q}_{t|t-1}$involves equations (4)–(6), where *K* is the gain of the Kalman filter, expressed in (6); *P* is the prediction error of the filter; *H* is the observation model and is defined as an identity in the equation; and $\boldsymbol{R}$ is the observation covariance matrix.

$$\vec{q}_{t|t} = \vec{q}_{t|t-1} + K \cdot (\vec{q}_t - \vec{q}_{t|t-1}) \tag{4}$$

$$P_{t|t-1} = (\mathrm{F} \cdot \mathrm{Q} \cdot F^T) + Q \tag{5}$$

$$K = P_{t|t-1} \cdot H \cdot (H \cdot P_{t|t-1} \cdot H^T + R)^{-1} \quad (6)$$

2) Quaternion to Euler Angle Conversion

Euler angles, required to track the patient's movement, can be transformed by the quaternion to Euler equations in (7).

$$\begin{bmatrix} Roll\ (\Phi) \\ Pitch\ (\theta) \\ Yaw\ (\psi) \end{bmatrix} = \begin{bmatrix} \tan^{-1}(\frac{2(q_0q_1+q_2q_3)}{1-2(q_1q_1+q_2q_2)}) \\ \sin^{-1}(2(q_0q_2 - q_1q_3)) \\ \tan^{-1}(\frac{2(q_0q_3+q_1q_2)}{1-2(q_2q_2+q_3q_3)}) \end{bmatrix} \quad (7)$$

3) Measurement of Force Sensitive Resistors

The 12-bit ADC inside the MCU converts the voltage value from the force sensitive resistors to digital output. The conversion of digital output D to output voltage V_{fsr} is expressed in (8), where the input voltage is 3.3 V.

$$V_{fsr} = \frac{3.3}{2^{12}} \cdot D \quad (8)$$

III. Results and Discussions

A. Attitude Estimation Precision

1) Verification of Data Validity

After the raw data from the IMU sensors is preprocessed, the data are compared with an inertial motion sensor (LPMS-B, LP-Research, Tokyo, Japan) to ensure that the raw data are correct. The 9-axis IMU sensor is tightly affixed beside the inertial motion sensor on the same plane and moved with the inertial motion sensor synchronously. The results showed that the output values of acceleration, angular velocity, and magnetic field were the same in the same status. The verification ensured that the raw data obtained from the sensors of the proposed data glove are reliable; thus, the system provides data on the acceleration, angular velocity, and magnetic field for physician use during hand rehabilitation.

2) Verification of Attitude Estimation

The static attitude estimation was confirmed using the goniometer. The bending angle was set to 30°, 45°, 60°, and 90° with two 9-axis IMU sensors to simulate the static step of finger movement. The results showed that the average error of the static bending angle was 0.98°, an amount that ensures that the accuracy of the attitude estimation algorithm. This error may have occurred because of the placement of the two sensors. The dynamic movement was confirmed using a servomotor. The bending angle was set to alternate between 30° and 60°, remaining for 2 seconds in each state. Fig. 4 shows the results of the dynamic movement verification. The 9-axis IMU sensors' movement was the same as that of the servomotor; thus, the accuracy of the algorithm was verified. The error in static attitude estimation can be ignored.

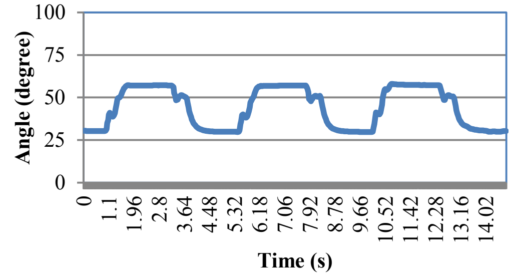

Fig. 4. Verification of dynamic movement.

3) Verification of Force Sensitive Resistor

After the force in the fingertip was measured, the force sensitive resistor was verified. A digital force gauge (DS-200, Desik, Karlsruhe, Deutschland) was used as the standard reference to ensure that the measured force was accurate. The results showed that the error of the measured force was less than 0.02 kg when compared with error obtained by the digital force gauge. This small error will not affect clinical tests. Thus, the measured force from the force sensitive resistors was valid, and the system can provide physicians with the correct force information from the fingertips.

4) Minnesota Manual Dexterity Test

In the clinical test, the Minnesota Manual Dexterity Test (MMDT) was conducted to assess hand function [21]. This test was used because it is simple and widely used by physicians to evaluate hand function in patients. The tasks for evaluating hand function in the MMDT involve flipping 60 cylinders. In this study, two participants underwent testing. One participant had normal hand function, and the other participant was a patient with stroke and could not perform the task smoothly. Figs. 5(a) and 5(b) show the changes in the bending angle of the distal interphalangeal on the index finger after normalization, which is the most critical when flipping the cylinders, in the normal participant and the patient, respectively. The red line in the figure indicates the average movement of angles in the 60 cylinder flipping task. The result showed that the normal user performed the flipping task smoothly. However, Fig. 5(b) shows that the patient with stroke could not perform the task smoothly; the 60 lines indicating the change in the bending angle are not consistently near the line denoting the average pattern. Thus, the patient flipped the cylinders erratically and had poorer hand function. Fig. 6 depicts the measured force of the fingertip of the index finger from both participants. The result showed that the normal participant picked up the cylinders lightly and steady; however, the patient picked up the cylinders with tremendously unstable force. Although the patient finished the tasks faster than did the normal participant, the quality of the movement was lower. This crucial information cannot be acquired using traditional hand function evaluation tools.

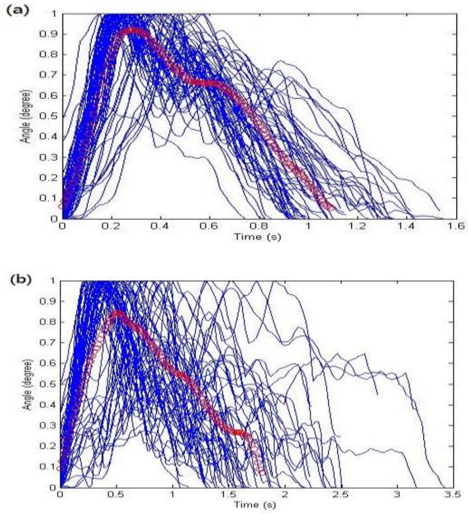

Fig. 5. (a) Data for participant with normal hand function and (b) patient with stroke.

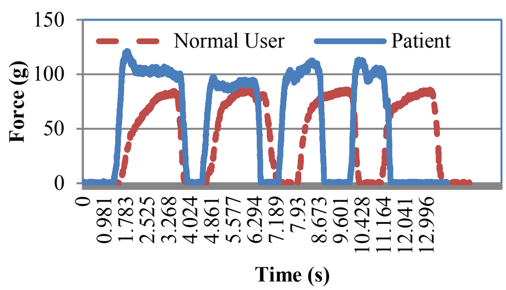

Fig. 6. Comparison of force in fingertip between normal participant and patient with stroke.

IV. Conclusion

According to the evaluations and experiments performed in this study, the proposed algorithm yields precise and credible output angle and force data.

This paper proposes a data-glove-based system embedded with 9-axis inertial sensors and force sensitive resistors to provide an accurate and flexible tool. This system can replace traditional hand function evaluation systems and resolve the problems encountered in previous studies, including limited flexibility and the inability to be adapted for all hand sizes or obtain information such as acceleration, velocity, finger bending angle, and fingertip force, during rehabilitation.

References

[1] H. Yamaura, K. Matsushita, R. Kato, and H. Yokoi, "Development of Hand Rehabilitation System for Paralysis Patient-Universal Design Using Wire-Driven Mechanism-," in *Proc. of the 31st Annual International Conference of the IEEE EMBS, Minnesota*, USA, 2009, pp. 7122–7125.

[2] Y. Park, J. Lee, and J. Bae, "Development of a finger motion measurement system using linear potentiometers," in *Proc. of 2014 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), Besançon*, France, 2014, pp. 125–130.

[3] Y. Fukuda, T. Tanaka, M. Q. Feng, and T. Ishimatsu, "MEMS and fiber optics sensor-based wearable interface for medical applications," in *Proc. of 2005 IEEE International Conference on Systems*, Man and Cybernetics, 2005, pp. 1675–1679.

[4] C. C. Cheng, I. Her, Q. H. Huang, and M. T. Wu, "A tele-monitoring system for performance evaluation of motor task in fMRI environment," in *Proc. of International Conference on Intelligent Sensors, Sensor Networks and Information Processing 2008*, Sydney, Australia, 2008, pp. 369–374.

[5] M. Nishiyama and K. Watanabe, "Wearable Sensing Glove With Embedded Hetero-Core Fiber-Optic Nerves for Unconstrained Hand Motion Capture," *IEEE Trans. Instrumentation and Measurement*, vol. 58, no. 12, pp. 3995–4000, November 2009.

[6] E. Fujiwara, Y. T. Wu, D. Y. Miyatake, M. F. M. Santos, and C. K. Suzuki, "Evaluation of Thumb-Operated Directional Pad Functionalities on a Glove-Based Optical Fiber Sensor," *IEEE Trans. Instrumentation and Measurement*, vol. 62, no. 8, pp. 2330–2337, July 2013.

[7] L. K. Simone, N. Sundarrajan, X. Luo, Y. Jia, and D. G. Kamper, "A low cost instrumented glove for extended monitoring and functional hand assessment," *Journal of Neuroscience Methods*, vol. 160, no. 2, pp. 335–348, March 2007.

[8] R. Gentner and J. Classen, "Development and evaluation of a low-cost sensor glove for assessment of human finger movements in neurophysiological settings," *Journal of Neuroscience Methods*, vol. 178, no. 1, pp. 138–147, March 2009.

[9] J. Zhou, F. Malric, and S. Shirmohammadi, "A New Hand-Measurement Method to Simplify Calibration in CyberGlove-Based Virtual Rehabilitation," *IEEE Trans. Instrumentation and Measurement*, vol. 59, pp. 2496–2504, September 2010.

[10] R. Vinjamuri, D. J. Crammond, D. Kondziolka, H. N. Lee, and Z. H. Mao, "Extraction of Sources of Tremor in Hand Movements of Patients With Movement Disorders," *IEEE Trans. on Information Technology in Biomedicine*, vol. 13, pp. 49–56, January 2009.

[11] N. P. Oess, J. Wanek and H. J. A. van Hedel, "Enhancement of bend sensor properties as applied in a glove for use in neurorehabilitation settings," in *Proc. of 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Buenos Aires, 2010, pp. 5903–5906.

[12] E. Szelitzky, A. M. Aluţei, B. Chetran, and D. Mândru, "Data glove and virtual environment — A distance monitoring and rehabilitation solution", in *Proc. of 2011 E-Health and Bioengineering Conference*, Iaşi, Romania, 2011, pp. 1–4.

[13] A. M. Ali, R. Ambar, M. M. A. Jamil, A. M. Wahi, and S. Salim," Artificial Hand Gripper Controller via Smart Glove for Rehabilitation Process," in *Proc. of 2012 International Conference on Biomedical Engineering*, Penang, Malaysia, 2012, pp. 300–304.

[14] M. Borghetti, E. Sardini, and M. Serpelloni, "Sensorized Glove for Measuring Hand Finger Flexion for Rehabilitation Purposes," *IEEE Trans. Instrumentation and Measurement*, vol. 62, pp. 3308–3314, November 2013.

[15] K. Grandez, G. Solas, P. Bustamante, and B. Sedano,"Sensor device for testing activities in Parkinson and ALS patients," in *Proc. of 2010 4th International Conference on Pervasive Computing Technologies for Healthcare*, Munich, Germany, 2010, pp. 1–6.

[16] S. A. Dalley, H. A. Varol, and M. Goldfarb, "A Method for the Control of Multigrasp Myoelectric Prosthetic Hands," *IEEE Trans. Neural Systems and Rehabilitation Engineering*, vol. 20, no. 1, pp. 58-67, January 2012.

[17] N. Oess, J. Wanek, and A. Curt, "Design and evaluation of a low-cost instrumented glove for hand function assessment," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, no. 1, pp. 1–26, January 2012.

[18] N. Carbonaro, G. Dalle Mura, F. Lorussi, R. Paradiso, D. De Rossi, and A. Tognetti, "Exploiting wearable goniometer technology for motion sensing gloves," *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 6, pp. 1788–1795, November 2014.

[19] H. Kortier, V. Sluiter, D. Roetenberg, and P. Veltink, "Assessment of hand kinematics using inertial and magnetic sensors," *Journal of NeuroEngineering and Rehabilitation*, vol. 11, no. 1, pp. 1–14, April 2014.

[20] D. Comotti and M. Ermidoro, *Report of the Course Progetto Di Miccroelettronica*, Bergamo, Italy, 2011.

[21] Lafayette Instrument. (1998). THE MINNESOTA DEXTERITY TEST Examiner's Manual. [Online]. Available: http://www.meetinstrumentenzorg.nl/Portals/0/bestanden/141_2_N.pdf