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3-D Hand Motion Tracking and Gesture Recognition Using a Data Glove

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Abstract **– Hand motion tracking and gesture recognition are a fundamental technology in the field of proactive computing for a better human computer interaction system. In this paper, we have developed a 3-D hand motion tracking and gesture recognition system via a data glove (namely the KHU-1 data glove consisting of three tri-axis accelerometer sensors, one controller, and one Bluetooth). The KHU-1 data glove is capable of transmitting hand motion signals to a PC through wireless communication via Bluetooth. Also we have implemented a 3-D digital hand model for hand motion tracking and recognition. The implemented 3-D digital hand model is based on the kinematic chain theory utilizing ellipsoids and joints. Finally, we have utilized a rule-based algorithm to recognize simple hand gestures namely scissor, rock, and paper using the 3-D digital hand model and the KHU-1 data glove. Some preliminary experimental results are presented in this paper.**

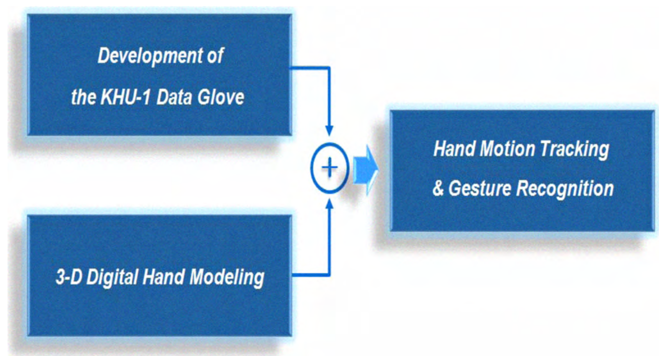

Fig.1. Fundamental Steps of Full System

I. INTRODUCTION

Recently, advanced human computer interaction (HCI) comes in spotlight for its potential use in the proactive processing device of an user`s information (e.g., thinking, touching, speaking, and motion): A proactive computing system that automatically recognize an user`s intention is essential for more advanced HCI [1]. Motion and gesture recognition is one key component in such a system [2], [3].

So far, motion recognition is mostly done by video and motion sensor-based approaches [4], [5]. The video sensor-based motion recognition uses the images from video sensor for recognition. Although this recognition method excels other recognition method in indoor activity, it has several restrictions such as space limitation, interruption of the light, and interference by environment [6], [7].

On the other side, the motion sensor based-motion recognition utilizes the signal of movement, such as acceleration from accelerometer and angular velocity from gyroscope sensors. The motion-sensor based motion recognition offers following advantages: i) because motion sensors are not affected by the surroundings, the motion sensor-based recognition is more suitable than the video sensor-based recognition in the complex environment and ii) it is attached to a user, thus providing more coverage, and iii) signals can be acquired wirelessly.

Data glove is one of such sensing devices in the sensor–based approach for hand motion and gesture recognition using motion sensors such as accelerometer, gyroscope, bend sensor, force sensor, and so on. Some recent works include i) Tarchanidis et al. [8] developed a data glove based on force sensors that are attached to each finger. This data glove was used to detect the tactile sensation, but it had limitations of hand motion tracking and precise recognition. ii) Bui et al. [9] developed a data glove based on two-axis accelerometers positioned on the back of the palm and each finger. However, hand gesture recognition using this device was only possible in two dimensions.

In this paper, we have developed a data glove that is composed of three tri-axis accelerometers, one controller, and one Bluetooth, and implemented a 3-D digital hand model. In addition, with the data acquired using our data glove, we have performed the rule-based hand motion tracking and gesture recognition.

II. DATA GLOVE

A. *Development of the KHU-1 Data Glove*

We have developed a data glove that is composed of three tri-axis accelerometers (Free Scale Inc.) [10] as the sensor of hand motion, an ATmega128 (AVR) as the controller [11], and FB755 Bluetooth (Firmtech Inc.) [12] as the wireless communication device. The output of tri-axis accelerometer is the analog signal that has a range of 0~3.3V. The accelerometer measures the acceleration using capacitance changes when an object is on the dynamic state. Also the accelerometer generates an offset value because of the influence of gravity when the object is on the static state. This

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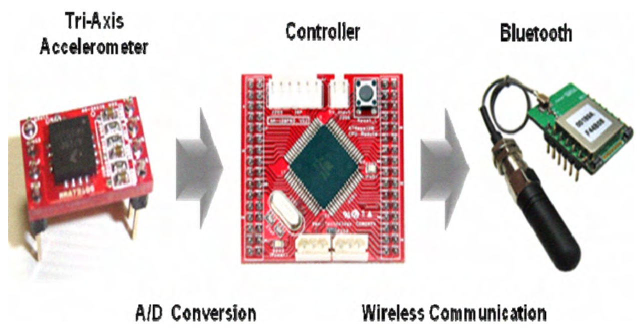


Fig.2. Accelerometer Signal Flow

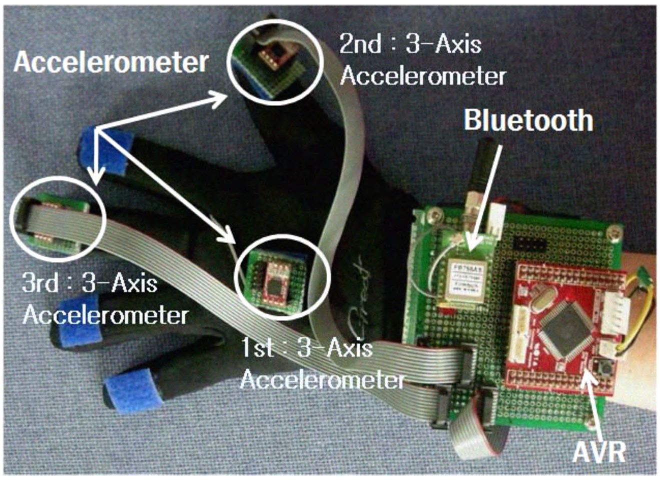


Fig.3. The KHU-1 Data Glove

offset value is useful in our proposed system since we can sense the tilt angle with respect to the device position.

For the analog to digital conversion of the signal, the sampling frequency was set to be 20-Hz that is sufficient to cover all movements of the hand motion and the quantization level was set to be 10-bit by predefinition of the controller. Fig. 2 shows the flow of the accelerometer signal.

This digitized signal is transmitted to a computer through the Bluetooth wireless communication. The Bluetooth supports the 9600 bit per second baud rate and is possible to the 1:8 multiple communication. Fig. 3 shows data glove that is consisted of the accelerometers, the controller and the Bluetooth. (Hereinafter referred to the KHU-1 data glove)

The KHU-1 data glove uses a rated voltage source for operating the sensors, controller, and Bluetooth. The operating voltage of the controller is 5V and both the sensor and Bluetooth use 3.3V. These voltages are generated by the bridge circuit and regulators of 5V and 3.3V respectively.

B. Data Acquisition and Display

In Fig. 4, data acquisition and display are according to the following procedures: i) acquisition of data of hand motion via the KHU-1 data glove, ii) transmission data to a PC. iii) evaluation of data received whether an error occurred or not

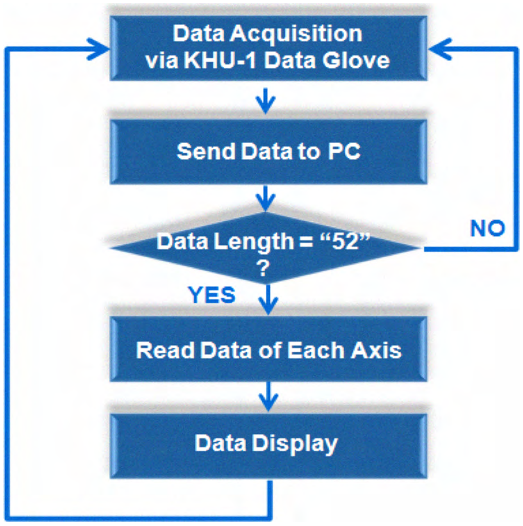


Fig.4. Data Acquisition and Display

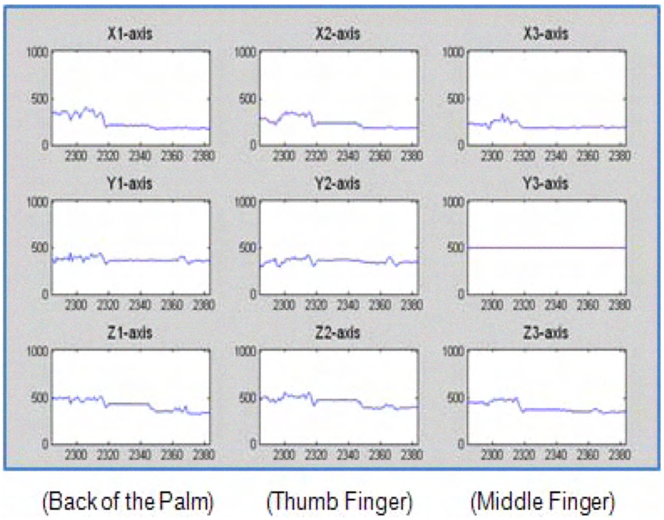


Fig.5. Display of Data Received through the KHU-1 Data Glove

through the received data length, iv) data acquisition and display under two conditions: (Condition 1) acquisition the case of successful transmission, data display; (Condition 2) when an error occurs, received data is ignored.

Fig. 5 shows the sample plots of the acquired data. Each column of graph indicates the back of the palm, thumb finger, and middle finger, and each row of graph indicates each axis to accelerometer (e.g., x-axis, y-axis, and z-axis).

III. 3-D Digital Hand Model

The kinematics is the science of the motion in which two objects are connected by a joint. This connected object is called a link. Usually the joint has one degree of freedom (DOF). However, it is possible to express the joint having n-

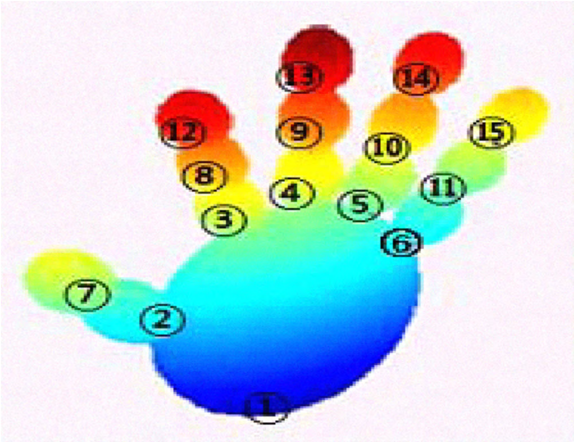
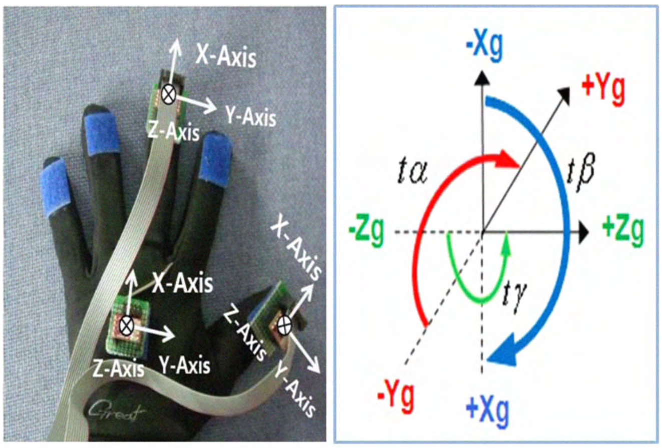


Fig.6. Our 3-D Digital Hand Model Using Ellipsoids



(a) (b)

Fig.7. Location and Coordinate of the Sensor on Glove

DOF through the n-1 links of zero length. We have implemented a 3-D digital hand model through the kinematic chain theory utilizing ellipsoids [13], [14]. Fig. 6 shows a 3-D digital hand model consisting of 15 ellipsoids which represent the volume of each knuckle, 15 joints, and skeletons. Each ellipsoid is expressed through the standard ellipsoid equation.

The hand model is implemented as connecting each neighboring ellipsoid. The joint is classified by the father-joint and child-joint depending on the father-joint and is located at both ends of the ellipsoid which is controlled by the father-joint. In other words, each ellipsoid forms a link by the joints. Therefore the ellipsoid is under the management of the joint which has a limited angle and DOF as a hand. For example, the joint of palm has a 0~180 degree limited angle and 2-DOF, but the joint of the middle finger has the 0~90 degree limited angle and 2-DOF.

IV. Hand Motion Tracking

A. *Coordinate of Sensor Motion Parameters*

Each tri-axis accelerometer is attached on the glove. Fig. 7 (a) shows the 3-axis of each accelerometer. The motion parameters, that are α, β, and γ, represent rotation angles of each axis as in Fig. 7 (b). We have performed several hand motions (e.g., stretching, bending, and clenching a fist) using only the β value which is the movement to the center of y-axis. So for representing these activities, we used only the β value and fixed the α and γ values. Equation (1) is the rotation matrix using α, β, and γ. In this work, α and γ are not in use so these value are set to zero, and the transmitting signal through the KHU-1 data glove uses the input of the β value only.

$$R = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\beta & 0 & \sin\beta \\ 0 & 1 & 0 \\ -\sin\beta & 0 & \cos\beta \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\gamma & -\sin\gamma \\ 0 & \sin\gamma & \cos\gamma \end{bmatrix}. \quad (1)$$

For the output of the KHU-1 data glove as the input of hand motion, the sensor outputs are normalized to 0~1 using (2) where *a* means the acceleration of each axis, *k* means the axis (e.g., x-axis, y-axis, and z-axis), and *n* represents the data sequence.

$$\text{normalized value} = \frac{a_{k[n]} - a_{k_{min}}}{a_{k_{max}} - a_{k_{min}}}. \quad (2)$$

The index finger, middle finger, ring finger, and little finger are controlled by one accelerometer attached on the middle finger for representing whole hand motion using only three accelerometers.

B. *Division by Default Angle*

One of the features of accelerometer is its different effect from gravity according to the angle of the sensor. We define the starting angle of hand motion as the default angle. When we apply the same algorithm for representing all angles causes the serious error. So we decide separating several cases according to the default angle using accelerometer on the back of the palm and use some different normalized axis output as the input of hand model considering each case. Fig. 8 represents three cases (e.g., Case 1: 0~45 degrees as the default angle; Case 2: 45~135 degrees as the default angle; Case 3: 135~180 degrees as the default angle). We performed hand motion tracking based on these cases.

i) Case 1: when the hand became from stretch to clench, the z-axis accelerometer output on the middle finger gradually increases. Thus it is possible to represent the hand motion using this normalized z-axis output as input of hand model. The joint to hand model is controlled by (3) using the β value obtained from the KHU-1 data glove. Equation (3) is used regardless of the default angle.

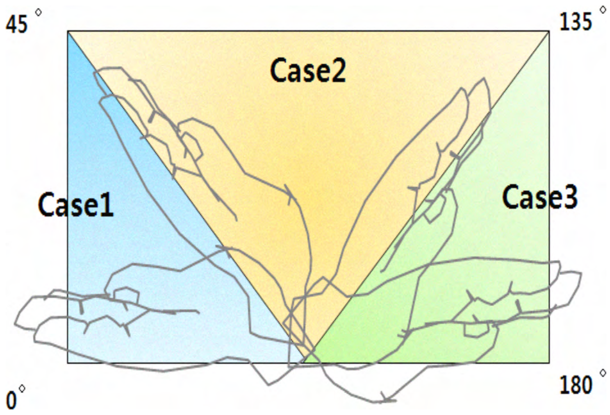


Fig.8. Three Cases by Default Angle to Hand

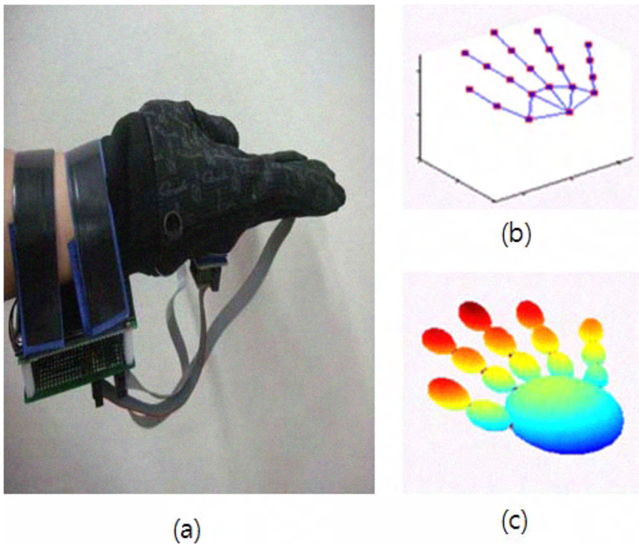


Fig.9. Stretching a Fist in Case 1
(a) Real Hand Motion, (b) skeleton Hand Model, and
(c) Ellipsoid Hand Model.

$$\begin{aligned} \text{joint(i)}.\beta &= \text{normalizated\_input\_value} \\ &\times (\text{joint(i)}.\beta_{\max} - \text{joint(i)}.\beta_{\min}) + \text{joint(i)}.\beta_{\min} \end{aligned} \tag{3}$$

where parameter i of (3) means the each joint number and joint(i). β means each β value of joint(i).

ii) Case 2: when default angle is between 45 and 135 degree, the direction of z-axis accelerometer on the middle finger is not equal to the direction of gravity. So the offset value of the z-axis accelerometer occurs on the default angle by influence of gravity. In this case when the fist clenching, using a z-axis output as an input of hand model has the serious problem that z-axis output changes from increase to decrease. So we have used the x-axis acceleration as the input to the hand model for representing the hand motion.

iii) Case 3; when the hand became from stretching to clenching, the z-axis accelerometer output on the middle finger gradually decreases. So, it is possible to representing the hand motion using the algorithm of Case 1.

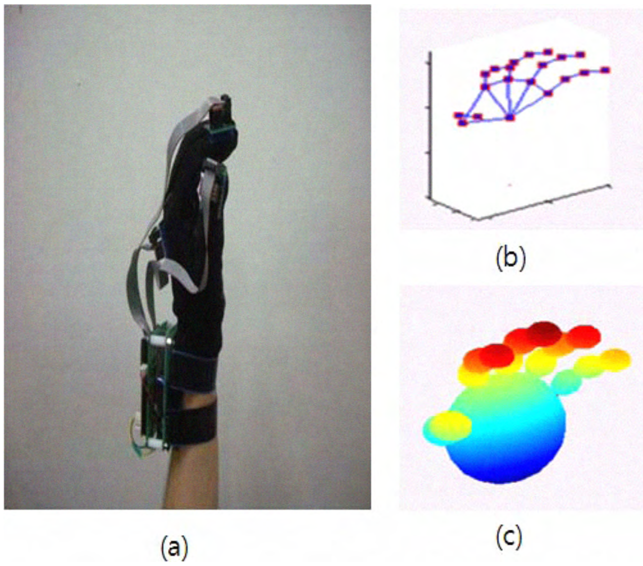


Fig.10. Bending a Fist in Case 2
(a) Real Hand Motion, (b) skeleton Hand Model, and
(c) Ellipsoid Hand Model.

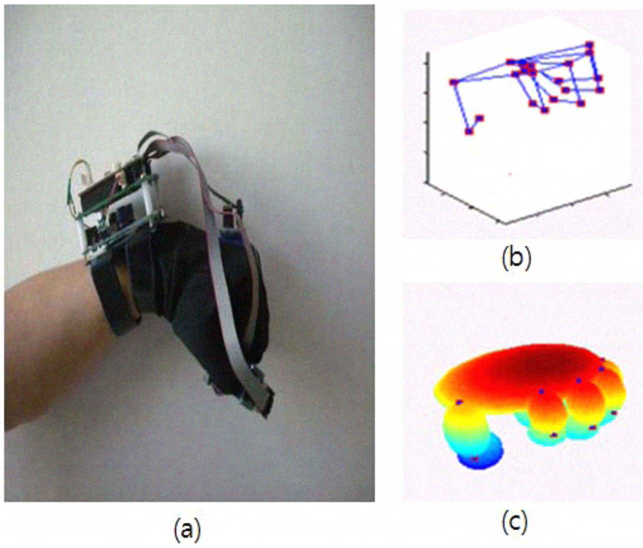


Fig.11. Clenching a Fist in Case 3
(a) Real Hand Motion, (b) skeleton Hand Model, and
(c) Ellipsoid Hand Model.

C. Hand Motion Tracking Results

Using the algorithm mentioned above, we have performed hand motion tracking such as fist clenching, stretching, bending, and bending only one thumb. Fig. 9, 10 and 11 are the sample results of hand motion tracking.

V. HAND GESTURE RECOGNITION

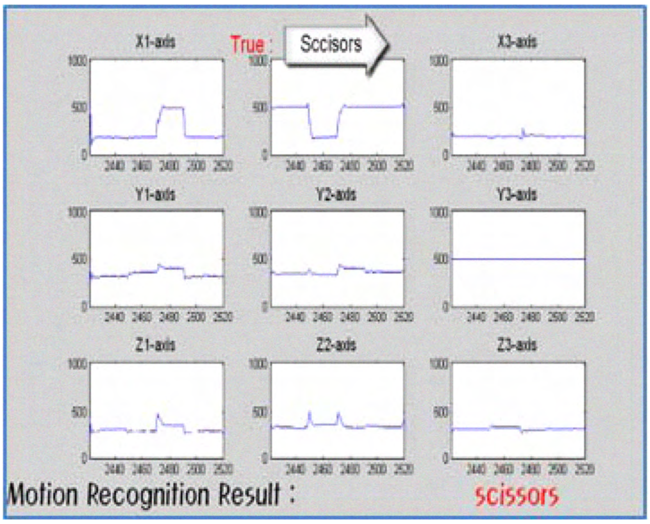


Fig.12. Real-time Hand Gesture Recognition Result

A. *Hand Gesture Recognition*

We perform the rule-based simple hand gesture (e.g., scissor, rock, and paper) recognition (HGR) at two different angular positions such as horizontal and vertical using the acceleration data through the KHU-1 data glove [15]. For two separate cases, accelerometer on the back of the palm is used. We use the different value each case for HGR such as:

i) Horizontal Gesture: Because of the z-axis of the sensor on the finger is the same direction as gravity, this value is used for gesture recognition.

ii) Vertical Gesture: Because of the x-axis of the sensor on the finger is the same direction as gravity, this value is used for gesture recognition.

For noise reduction, a 10-point moving average filter in (4) is used.

$$A_{k\_avg[i]} = \frac{\sum_{n=0}^{9} k[i-9]}{10} \quad (4)$$

where the parameter k means each axis (e.g., x-axis, y-axis, and z-axis) and i represents the data index.

B. *Hand Gesture Recognition Results*

We have preformed experiments of HGR using the KHU-1 data glove. Fig. 12 shows the exemplary results of real time hand gesture recognition and Table I is the recognition rate.

VI. Conclusion

In this paper, we present a 3-D hand motion tracking and gesture recognition via the KHU-1 data glove and the 3-D digital hand model. The KHU-1 data glove is capable of capturing hand motion via tri-axis accelerometer sensors through wireless communication between the data glove and a PC. We have performed some simple hand gesture recognition (e.g., scissor, rock, and paper) in the study.

Future work requires faster computation time to reduce the time delay of the system and advanced recognition methods to recognize more complex gestures.

TABLE I
Hand Gesture Recognition Rate

Activities	Trial Number	Recognition Rate
Scissor	50	100%
Rock	50	100%
Paper	50	100%

Acknowledgments

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