Method to Use Low-priced Data-glove Effectively Based on Medical Knowledge for Hand Motion Pattern

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***Abstract*—A data glove is one of the major interfaces used in the field of virtual reality. In order to get detailed data about the finger joint angles, we must use a data glove with many sensors. However, a data glove with many sensors is expensive and a low-priced data glove does not have enough sensors to capture all the hand data correctly. We propose a method to obtain all finger joint angles by estimating the pattern of hand motion from the low-priced data glove sensor values. In our experiment system, we assumed some representative hand motion patterns as grasping behavior based on medical knowledge. We also assumed that other hand motions can be represented by synthetic motion of the representative patterns. In this paper, we used the data glove with sensors covering two joints of each finger. And we also estimate the finger joint angles when using the data glove that sensors cover only the middle angle of each finger.**

Keywords–Data-glove; Hand motion estimation; Finger joint angles estimation; Medical knowledge.

I. INTRODUCTION

Virtual Reality (VR) is a rapidly growing research field in recent years. VR technologies give us various advantages. There are simulators to practice an operation and to fly a plane as examples of VR technologies. These simulators enable us to avoid the risk and to save on cost. VR researches that targets to households also have been attracted. A data glove is one of the major interfaces, which are used in the field of VR. It measures curvatures of fingers using bend sensors. In our laboratory, we propose a method to get plausible user hand motion pattern from the low-cost glove [1]. In our first work, we use 5DT Data Glove (see Figure 1) whose sensors cover two joints of each finger. Then, we estimate finger joint angles when using the data glove DG5 VHand (see Figure 2) whose sensors cover only the middle angle of each finger.

The rest of the paper is structured as follows. In Section II, we present a state of the art of data gloves. In Section III, we describe a method how to estimate finger joint angels. In Section IV, we describe about representative hand motion patterns based on medical knowledge. In Section V, we apply this method to the data-glove whose sensor positons are limited. In Section VI, the experimental results are shown. In Section VII, we consider the difference between users' hand shapes. In Section VIII, the experimental results for hand shape are shown. Finally, we conclude in Section IX.

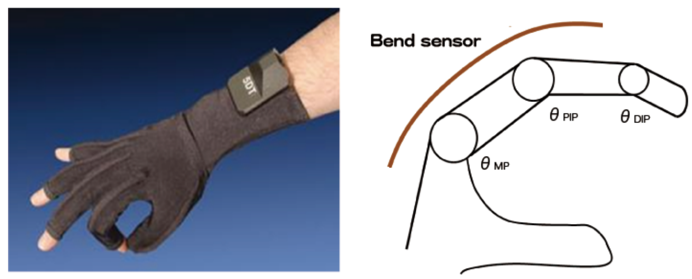

Figure 1. 5DT Data Glove 5 Ultra

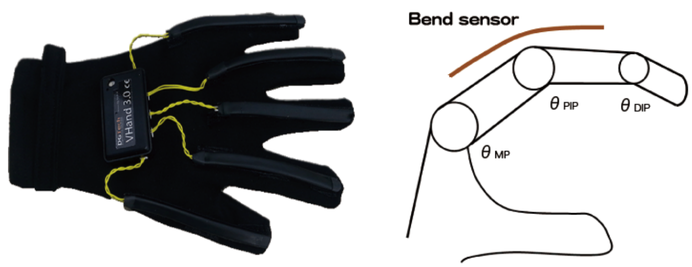

Figure 2. DG5 VHand

II. STATE OF THE ART

In order to obtain accurate hand motions, it is necessary to use a data glove, i.e. Immersion CyberGlove, which has many sensors, but it is expensive. It is preferable that an interface is small scale and low cost. Various types of researches about data glove have been conducted [2][3][4][5]. On the other hand, there is a low cost data glove, which measures an angle for each finger through one sensor. But it cannot get detailed data directly. For example, the 5DT Data Glove 5 Ultra and DG5 VHand have a single sensor on each finger, so they have five sensors in the whole hand (see Figures 1 and 2). However, there are three finger joints for each finger, a single sensor can not measure all of these three angles directly.

Our proposed novel method estimates the kind of hand motion patterns using each relation among angles of fingers

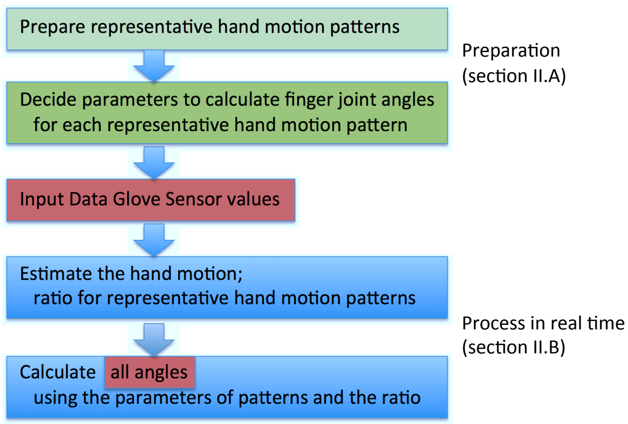

Figure 3. Overview of method

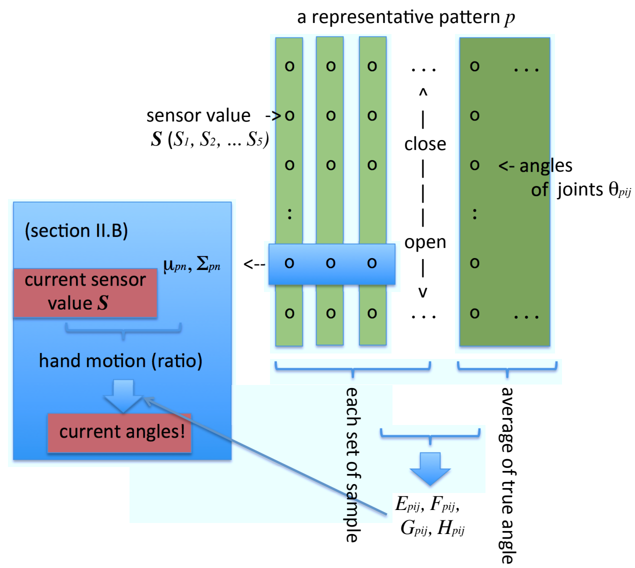

Figure 4. Detail of method

during operation. Then, it estimates all finger joint angles by estimating the types of hand motion patterns from the correlation between each finger angle in the hand motion pattern. We assume some representative hand motion patterns based on medical knowledge [6], and consider that other hand motions can be represented as a synthetic motion of the representative hand motion patterns. In addition, we calculate the ratio of each representative motion pattern. Moreover, estimating each finger angle using the result, we express any hand motion patterns other than the representative hand motions.

III. Estimation of Finger Joint Angles

In Section III, we describe an estimation method of finger joint angles using 5DT data glove, which is developed in our laboratory (see Figure 3).

A. Representative Hand Motion Patterns

To estimate finger joint angles, this method limits user's hand motion to grasping motion. First of all, we had set the three representative hand motions as grip, pinch and nip.

Furthermore, we assume that a human's grasping motion can be represented as a synthetic motion of representative hand motion patterns. To derive three finger joint angles from a single sensor value, we use the following method (see Figure 4). We sample many sets of the sensor values with the low-priced data glove when some subjects open their hand first and then close it to each representative hand motion patterns. Also, we sample the sets of the true angles of finger joints for the same representative patterns, provided that we use true angles obtained from a data glove, which has a lot of sensors. We use Immersion CyberGlove as data glove with a lot of sensors. Then, the sensor values and the true angles of finger joints at the same time are associated. We show an example of correspondence in Figure 5.

We derive the following numerical formulas using this correspondence.

$$\theta_{pi1} = \frac{2}{3}\theta_{pi2} \quad (1)$$
$$\theta_{pi2} = E_{pi2}S_i^3 + F_{pi2}S_i^2 + G_{pi2}S_i + H_{pi2} \quad (2)$$
$$\theta_{pi3} = E_{pi3}S_i^3 + F_{pi3}S_i^2 + G_{pi3}S_i + H_{pi3} \quad (3)$$

where pattern p is one of representative hand motion patterns. Angles θ_{pi1}, θ_{pi2} and θ_{pi3} express the DIP, PIP, and MP joint angle of the finger i for the pattern p. The DIP, PIP, and MP joint mean the first, second and third joint of a finger respectively. The S_i is sensor value of finger i. And E_{pij}, F_{pij}, G_{pij} and H_{pij} are constant parameters for the pattern p, finger i and joint j. These parameters, E_{pij} to H_{pij}, are calculated by pre-experiment. Besides, DIP joint angle is obtained by proportional connection with PIP joint angle (equation (1)) [7]. Joint angles of finger i of pattern p are obtained by these numerical formulas.

B. Hand Motion Estimation and Angles Estimation

To represent user's hand motion as synthetic motion of representative hand motion patterns, we need to know how similar the user's hand motion is and to which representative hand motion patterns. Then, we set the following formula based on the probability density function of the multivariate normal distribution for n points in the five dimensional feature amount space.

$$L_{pn} = exp\{-\frac{1}{2}(\boldsymbol{S}-\boldsymbol{\mu}_{pn})^T\boldsymbol{\Sigma}_{pn}^{-1}(\boldsymbol{S}-\boldsymbol{\mu}_{pn})\} \quad (4)$$

where $\boldsymbol{S}$ is the sensor value vector. And $\boldsymbol{\mu}_{pn}$ and $\boldsymbol{\Sigma}_{pn}$ represent mean vector of sensor sample values, and variance-covariance matrix of sample point n (an integer satisfying $1 \leq n \leq$ a number of samples) in representative hand motion pattern p. Besides, $\boldsymbol{\mu}_{pn}$ and $\boldsymbol{\Sigma}_{pn}$ are obtained by pre-experiment for an average user. If the sensor values are obtained actually

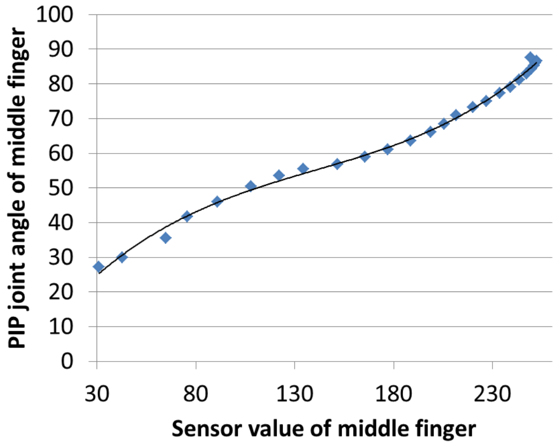

Figure 5. Example of correspondence

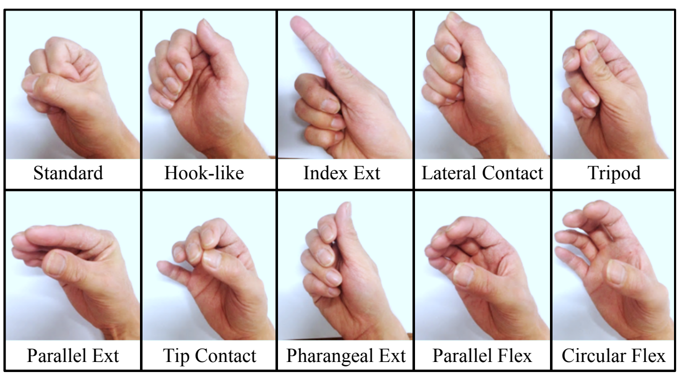

Figure 6. Candidates of representative motions

from the glove, we select the maximum value according to the following formula.

$$L_p = \max_n \{L_{pn}(\boldsymbol{S} : \boldsymbol{\mu}_{pn}, \boldsymbol{\Sigma}_{pn})\} \tag{5}$$

Thus, we get the likelihood on representative hand motion pattern p in current sensor values. After that, we decide the ratio r_p of hand motion pattern p according to the following formula.

$$r_p = \frac{L_p}{\Sigma_{p=1}^{P} L_p} \tag{6}$$

where P is the total number of representative hand motions, which takes the value of four. As stated above, we can obtain θ_{pij} and r_p. At last, each angle θ_{ij} of current hand posture is derived by the following formula.

$$\theta_{ij} = \sum_{p=1}^{P} r_p \cdot \theta_{pij} \tag{7}$$

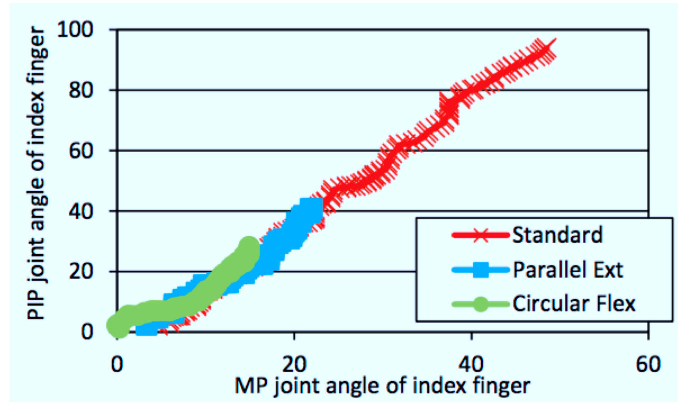

Figure 7. Example of MP and PIP Joint Angle of Index Finger

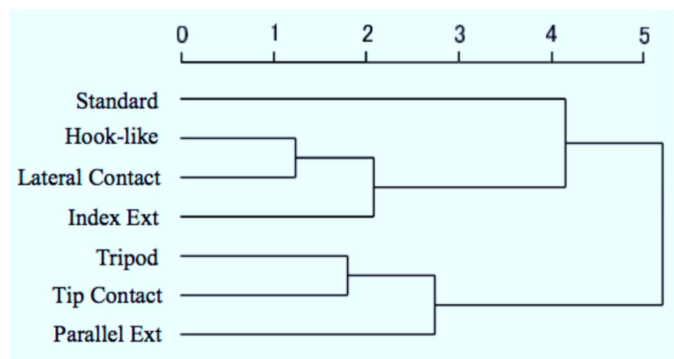

Figure 8. Dendrogram of the Candidata 1

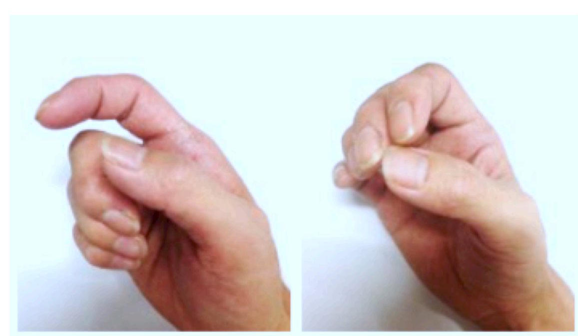

Figure 9. Average Hand Motions (left: MC_2, right: MC_3)

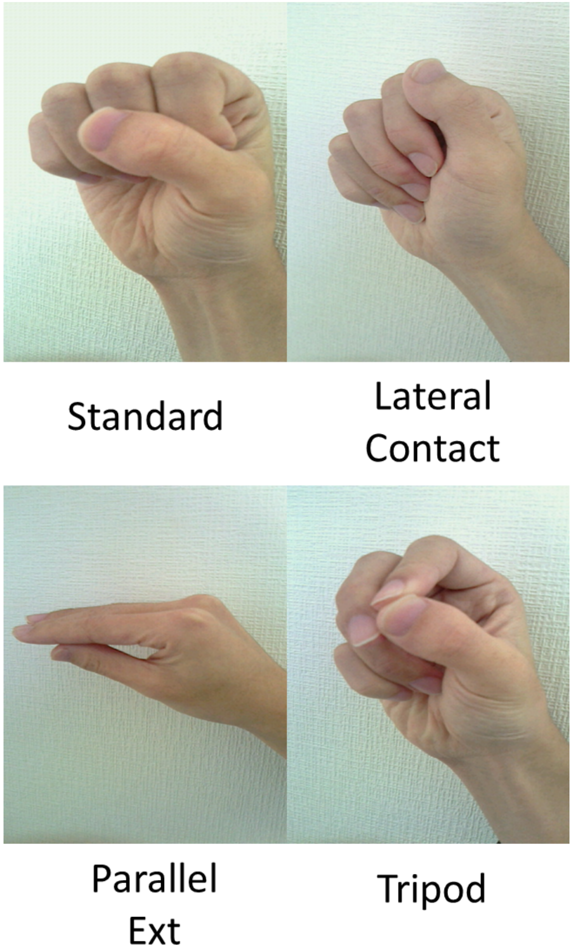

Figure 10. Representative hand motion patterns

IV. Reconsider Representative Hand Motions

In Section IV, we reconsider the representative hand motion patterns based on medical knowledge.

A. Candidate Selection

We reconsider them through the research on the grasping behavior of human hand [8]. They had observed daily grasping forms in experimental condition and classified them into 14 types to help reference in clinical. We select 10 candidates as representative hand motion from these 14 types, because they change enough sensor values of a data-glove respectively (Figure 6). And we obtained the transitions of each finger joint angle of the 10 motions from open hand to each form using data-glove, which has many sensor (CyberGlove). It was also confirmed that Parallel Flex and Circular Flex can be represented in a part of Standard (Figure 7), and Phalangeal Ext can be represented in a part of Lateral Contact. Therefore, we selected 7 motions as representative ones of candidate No.1.

B. Candidate Reduction

If one of the representative hand motions is similar to another one, it may not occur good estimation. If the number of the motions of candidate 1 can be reduced with enough result,

TABLE I. JOINT ANGLE ERROR (INPUT: REPRESENTATIVE ONE) [DEGREE]

	thumb	index	middle	ring	little	average
Candidate 1	8.3	5.7	3.9	3.4	6.5	5.6
Candidate 2	5.9	2.5	3.2	4.9	3.0	3.9
Candidate 3	7.2	4.2	3.2	4.5	4.2	4.7

TABLE II. JOINT ANGLE ERROR (INPUT: EXCEPT REPRESENTATIVE ONE) [DEGREE]

	thumb	index	middle	ring	little	average
Candidate 1	8.5	9.4	9.1	6.5	18.5	10.4
Candidate 2	9.4	9.6	9.6	6.5	17.55	10.5
Candidate 3	8.2	8.7	8.7	7.4	12.22	9.0

we can remove the redundant computation. So, we sampled the sensor values for the candidate 1 and standardize them (mean 0 and variance 1). Then we performed hierarchical cluster analysis for them using the ward method to create a dendrogram about the candidate 1 (Figure 8). The hand motions were classified into 4 classes based on the cutting point 2.5 as a middle distance. The classes are defined as following; C_1: Standard, C_2: Hook-like, Lateral Contact, Index Ext, C_3: Tripod, Tip Contact, and C_4: Parallel Ext. Thereby Standard, Lateral Contact, Tripod and Parallel Ext were selected as candidate No.2 according to the score. Furthermore we constructed average hand motions MC_2 and MC_3 for the classes C_2 and C_3 respectively (Figure 9), and obtained candidate No.3.

C. Confirmation Experiment

We had experiment for the three candidates using the 5DT Data Glove 5 Ultra, which has a bend sensor for each finger. When the input data are the representative motions in this experiment, the averages of estimated ratio r_p are; candidate 1: 0.83, candidate 2: 0.86, and candidate 3: 0.95. We can also confirm the average of candidate 3 is higher than the average 0.92 of conventional system with first representative hand motions as grip, pinch and nip. Table I shows the average of the errors of DIP, PIP and MP between estimated finger joint angles and obtained angles by CyberGlove. The input data is Tripod motion for candidate 1 and 2, and MC_2 for candidate 3. Table II shows the error when the input motion data is not representative one for each candidate, that is, the input data is MC_2 motion for candidate 1 and 2, and Tripod for candidate 3. We confirmed that the error of candidate 3 is smallest for the average of both results, and it can deal with any hand motions other than the representative ones. Therefore, we found that candidate No.3 is the most suitable for representative hand motions, and candidate No.2 is the second suitable one.

V. Data-glove whose Sensor Positions are Limited

In Section V, we describe an estimation method of finger joint angles using DG5 data glove whose sensor positions are limited only to PIP joints.

A. MP Angle for Representative Hand Motion Pattern

Although we mentioned above a set of representative hand motion patterns is selected as candidate No.3, the pattern Parallel Ext is almost the motion related only to MP joints. When doing the Parallel Ext pattern, the sensor values hardly change. We tentatively use three other patterns as representative hand motion patterns except Parallel Ext from the candidate No.2 (Figure 10) for now.

For the 5DT data glove whose sensors cover PIP and MP joints, the DIP angle is related to PIP directly, as mentioned in the Section III. It means the sensor values contain all of their information. However, using DG5 whose sensors are only on PIP, the motion of MP does not change the sensor value. Of course, we assume that the hand motion is a grasping one, so the MP angle of a finger is related to the PIP angle of the same finger. Then we can assume that the MP of a finger is related to the PIPs of all fingers.

We consider a new estimation model to obtain angles for representative hand motion patterns using multiple regression analysis. First, we make a estimation equation with explanatory variable is a set of sensor values, and response variable is each MP joint angle, as follows.

$$\theta_{pi3} = \sum_{f=1}^{5} C_{pif3} S_f + I_{pi3} \tag{8}$$

where θ_{pi3} is MP joint angle of finger i of representative pattern p, S_f is sensor value of finger f, and C_{pif3} and I_{pi3} are constant.

Now, a subject opens his hand first and then closes it to each representative pattern with DG5 data glove, the set of sensor value $S_f(time)$ of finger f at $time$ is sampled. Then, the subject moves his hand as each same pattern with CyberGlove, which has many sensors, the set of angle value $\theta_{pi3}(time)$ is sampled as true one.

Here, we should get the constant C_{pif3} and I_{pi3}. The residual sum of squares Q is represented as in (9).

$$Q = \sum_{time} \left\{ \theta_{pi3}(time) - \left(\sum_{f=1}^{5} C_{pif3} S_f(time) + I_{pi3} \right) \right\}^2 \tag{9}$$

Focusing on coefficient C_{pi13} where $f = 1$;

$$\begin{aligned} Q = \sum_{time} \Bigg\{ & \big(S_1(time) C_{pi13}\big)^2 \\ & + 2 S_1(time) C_{pi13} \left(\sum_{f=2}^{5} C_{pif3} S_f(time) + I_{pi3} \right) \\ & - 2\theta_{pi3}(time) S_1(time) C_{pi13} \\ & + \left(\sum_{f=2}^{5} C_{pif3} S_f(time) + I_{pi3} \right)^2 \\ & - 2\theta_{pi3}(time) \left(\sum_{f=2}^{5} C_{pif3} S_f(time) + I_{pi3} \right) \\ & + \big(\theta_{pi3}(time)\big)^2 \Bigg\} \end{aligned} \tag{10}$$

Using the partial differentiations with C_{pi13};

$$\begin{aligned} \frac{\partial Q}{\partial C_{pi13}} = 2 \sum_{time} S_1(time) \Bigg\{ & \sum_{f=1}^{5} C_{pif3} S_f(time) \\ & + I_{pi3} - \theta_{pi3}(time) \Bigg\} \end{aligned} \tag{11}$$

Using the partial differentiations also with C_{pif3} and I_{pi3};

$$\begin{aligned} \frac{\partial Q}{\partial C_{pif3}} = 2 \sum_{time} S_f(time) \Bigg\{ & \sum_{f'=1}^{5} C_{pif'3} S_{f'}(time) \\ & + I_{pi3} - \theta_{pi3}(time) \Bigg\} \end{aligned} \tag{12}$$

$$\begin{aligned} \frac{\partial Q}{\partial I_{pi3}} = 2 \sum_{time} \Bigg\{ & I_{pi3} + \sum_{f=1}^{5} C_{pif3} S_f(time) \\ & - \theta_{pi3}(time) \Bigg\} \end{aligned} \tag{13}$$

The constant C_{pif3} and I_{pi3} to be obtained make Q represented as the minimum of the equation from (9). And the C_{pif3} and I_{pi3} that make Q minimum satisfy following equation.

$$\frac{\partial Q}{\partial C_{pif3}} = \frac{\partial Q}{\partial I_{pi3}} = 0 \tag{14}$$

Solving this, coefficient C_{pif3} and constant I_{pi3} are obtained to estimate MP joint angle for representative pattern with (8). The angles of PIP are obtained directly from the sensor value with (2), and the angles of DIP are also obtained only from PIP with (1).

B. Hand Motion Estimation with Pseudo-Inverse Matrix

When the variance of sensor values is zero at the sample point n of representative hand motion pattern, the variance-covariance matrix will be abnormal at the sample point n. It means the inverse matrix of variance-covariance matrix of sensor values $\boldsymbol{\Sigma}_{pn}^{-1}$ can not be obtained, and the likelihood for the sample data of representative pattern p can not be obtained with (4).

So, we use Moore-Penrose pseudo-inverse matrix to solve it. The variance-covariance 5×5 matrix of sensor values $\boldsymbol{\Sigma}_{pn}^{-1}$, which is abnormal at the sample point n is represented as next equation with $5 \times r$ matrix $\boldsymbol{A}_{pn}$ and $r \times 5$ matrix $\boldsymbol{B}_{pn}$ where $\operatorname{rank}(\boldsymbol{\Sigma}_{pn}) = r$;

$$\boldsymbol{\Sigma}_{pn} = \boldsymbol{A}_{pn} \boldsymbol{B}_{pn} \tag{15}$$

Here the Moore-Penrose pseudo-inverse matrix $\boldsymbol{\Sigma}_{pn}^{+}$ for $\boldsymbol{\Sigma}_{pn}$ is described as:

$$\begin{aligned} \boldsymbol{\Sigma}_{pn}^{+} &= \boldsymbol{B}_{pn}^{T} \left(\boldsymbol{A}_{pn}^{T} \boldsymbol{\Sigma}_{pn} \boldsymbol{B}_{pn}^{T} \right)^{-1} \boldsymbol{A}_{pn}^{T} \\ &= \boldsymbol{B}_{pn}^{T} \left(\boldsymbol{B}_{pn} \boldsymbol{B}_{pn}^{T} \right)^{-1} \left(\boldsymbol{A}_{pn}^{T} \boldsymbol{A}_{pn} \right)^{-1} \boldsymbol{A}_{pn}^{T} \end{aligned} \tag{16}$$

Using this Moore-Penrose pseudo-inverse matrix $\boldsymbol{\Sigma}_{pn}^{+}$ for (4) instead of the inverse matrix of variance-covariance matrix of


(1) Power grasp

(2) Precision grasp

(3) Lateral grasp

(4) Extension grasp

(5) Tripod grasp

(6) Index pointing

(7) Basic gestures

Figure 11. Hand motions needed for ADL

sensor values $\boldsymbol{\Sigma}_{pn}^{-1}$ at the sample point n where inverse matrix can not be defined, the likelihood is obtained and the ratio of each hand motion pattern is determined with (5) and (6), respectively. Now, we can use a low-priced data glove whose sensors cover only the middle angle of each finger to estimate all finger joint angles of current hand posture with (7).

VI. Experiment and Result

We performed an experiment to confirm the effectiveness of the method described above. The experiment system was constructed using the DG5 Data Glove whose sensor positions are limited only on middle joints. Other hand motions that were different from representative patterns were tested. The minimum of Activities of Daily Living (ADL) needs the following hand motions (see Figure 11) [9].

1) Power grasps (used in 35% ADLs)
2) Precision grasps (30% ADLs)
3) Lateral grasps (20% ADLs)
4) Extension grasps (10% ADLs),
5) Tripod grasps,
6) Index pointing, and
7) Basic gestures.

We tested five motions; 1)–5).

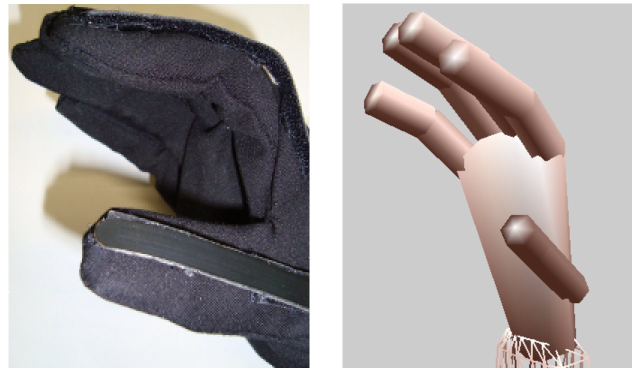

Figure 12. Result CG for Power grasp

Figure 13. Result CG for Precision grasp

The subjects opened their hands and then closed them to each test pattern 1)–5) with DG5 data glove. The average of estimated joint angles were compared with the true angles obtained from CyberGlove, which had many bend sensors.

Table III shows the average error of finger joint angles. Each error is around 10 degrees. The result using the 5DT data glove whose sensors cover two joints of each finger also had about 10 degrees error [6]. This means that the lower-priced data glove can obtain joint angles accurately enough.

Actual hand posture images and the CG images generated from estimated joint angles are shown in Figures 12 and 13. The MP joints that were not covered with bend sensors are estimated from the sensors on PIP joints.

VII. Difference of Hand Shape

In the method stated in previous sections, parameters are needed to be precomposed for each user. However, using an

TABLE III. ERROR OF FINGER JOINT ANGLES [DEGREE]

	thumb	index	middle	ring	little	average
Power G.	7.3	12.0	10.5	12.5	10.0	10.5
Precision G.	8.1	9.2	7.2	7.0	6.8	7.7
Lateral G.	9.4	6.0	8.8	7.5	10.5	8.4
Extension G.	9.8	8.1	11.0	11.3	9.0	9.9
Tripod G.	8.5	8.5	7.2	11.6	10.9	9.3
average	8.6	8.7	8.9	10.0	9.4	9.2

expensive glove to obtain the true angles of finger joints is not suitable from perspective of utilization in ordinary home. Furthermore, parameters to calculate angles are obtained by a lot of trials of hand motions. They are troublesome for general user. In this section, we try to determine the parameters automatically for motion and angles estimation.

A. Estimation Accuracy between Different Users

We investigated estimation accuracy between different users. With the cooperation of three research participants, we had an experiment. In this experiment we asked each participant to grasp a plastic bottle ($500ml$) with equipped data glove. The reason to choose this grasping motion was user's hand motion is little by little different every time even if user thinks that one performs the same hand motion. And we defined the hand size of user as H_{size}, which is decided by the distance from the wrist to the top of the middle finger (Figure 14). The H_{size} of each participant is shown in Table IV. The sample person is who provided each parameter for estimation in pre-experiment. And the parameters for estimation were obtained by the sample person's hand. When each participant grasped the plastic bottle, their finger joint angles were estimated by these parameters of sample person. We measured finger joint angles when their hand was touching completely with the plastic bottle. And we investigated the average of the errors between estimated finger joint angles and obtained angles by CyberClove. Table V shows the results. These results indicate that estimation accuracy using parameters of the person whose hand size is different becomes worse. We expected that joint angle errors of the sample person was minimum because sample person's parameters were used for estimation. However the average error of participant 2 was minimum in Table V. We concluded that the reason was the sensor values were not uniform but also scattering when user moved one's hand. However, only because of these numerical values, the results can not be judged whether they are significant or not. Then we had statistical hypothesis testing to confirm these results are significant. At this time, we adopted Student's t-test. We had Student's t-test to the average of joint angle errors of the sample person and other participants. Test statistic t_0 is obtained from the following formula.

$$t_0 = \frac{|\bar{X} - \bar{Y}|}{\sqrt{U_e(\frac{1}{m} + \frac{1}{n})}} \tag{17}$$

where $\bar{X}$ and $\bar{Y}$ are the average of joint angle errors, m and n represent the sample size of two groups. And U_e is obtained from the following formula.

$$U_e = \frac{(m-1)U_x + (n-1)U_y}{m+n-2} \tag{18}$$

where U_x and U_y are unbiased variance. As stated above, test statistic t_0 can be obtained and t_0 follows t-distribution. P-values obtained from Student's t-test are shown in Table VI. The $P(T \leq t)$ represents significance probability. In this paper, we decide that significance level α is 0.05. So, it is statistical significance if $P(T \leq t)$ is smaller than 0.05. Looking at Table VI, the $P(T \leq t)$ in all categories are smaller than 0.05. They indicate that there are statistical significance in estimation accuracy between the sample person and other participants. We confirmed necessity of determining parameters for each user.

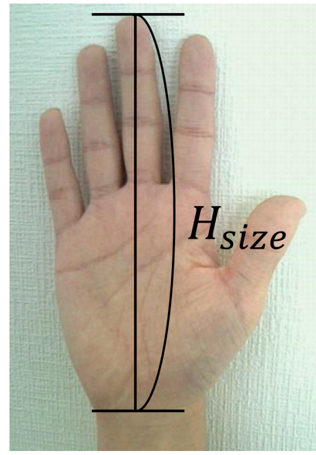

Figure 14. Definition of hand size

TABLE IV. H_{size} OF EACH PARTICIPANT [cm]

	H_{size}	standard deviation
participant 1	17.0	-
participant 2	18.1	-
participant 3	20.5	-
sample person	17.7	-
average of Japanese male [10]	18.3	0.8
average of Japanese female [10]	16.9	0.7

B. Hand Size Estimation

We assume that parameters to calculate finger joint angles are determined by knowledge of user's H_{size}. To evaluate user's H_{size}, we try to use the sensor values when user performs one hand motion. When deciding hand motion for estimation of hand size, it is important that a hand motion is simple. If it is obscurity motion, there is difficulty in performing hand motion. Then, we consider the total value of five sensors when user closes hand (=S_{total}). We obtained S_{total} and each H_{size} from each research participant. The correspondence between H_{size} and S_{total} is shown in Figure 15. Then we conclude the following formula.

$$H_{size} = aS_{total} + b \tag{19}$$

where a, b are constant parameters. Using this formula, user's H_{size} can be obtained by performing the simple hand motion.

TABLE V. JOINT ANGLE ERROR OF GRASPING PLASTIC BOTTLE [DEGREE]

	Thumb	Index	Middle	Ring	Little	avg.
sample	7.6	17.9	11.2	16.2	14.8	13.6
participant 1	31.1	17.7	26.4	5.0	5.1	17.1
participant 2	15.3	17.7	11.6	11.7	5.0	12.3
participant 3	30.2	10.5	27.2	17.7	17.7	20.7

TABLE VI. P-VALUES OF STUDENT'S T-TEST

	$P(T \leq t)$
participant 1	6.8×10^{-6}
participant 2	1.0×10^{-2}
participant 3	9.6×10^{-4}

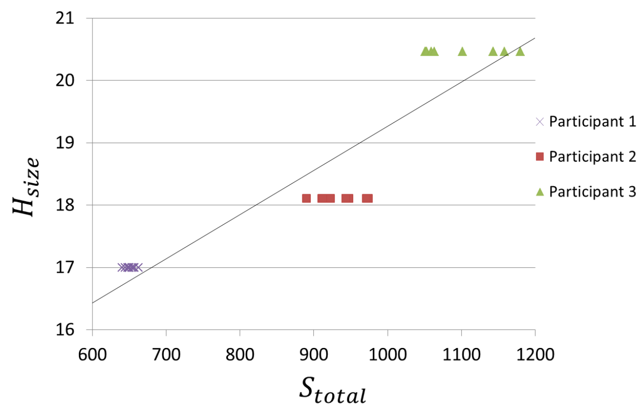

Figure 15. Relation between H_{size} and S_{total}

C. Determination of Estimation Parameters

We would like to determine the estimation parameters of new user whose H_{size} is h_u. The size h_u is obtained by (19). If two of the three participants are A and B, each hand size is h_A and h_B respectively ($h_A > h_B$), the parameters for h_u user are defined as below.

$$E_{upij} = \frac{(h_u - h_B)E_{Apij} + (h_A - h_u)E_{Bpij}}{h_A - h_B} \tag{20}$$

$$F_{upij} = \frac{(h_u - h_B)F_{Apij} + (h_A - h_u)F_{Bpij}}{h_A - h_B} \tag{21}$$

$$G_{upij} = \frac{(h_u - h_B)G_{Apij} + (h_A - h_u)G_{Bpij}}{h_A - h_B} \tag{22}$$

$$H_{upij} = \frac{(h_u - h_B)H_{Apij} + (h_A - h_u)H_{Bpij}}{h_A - h_B} \tag{23}$$

Of course the parameters E_{Apij} to H_{Apij} and E_{Bpij} to H_{Bpij} for h_A and h_B participants are calculated previously using expensive data glove (parameters for another participant are also calculated). Then numerical formula for estimation of finger joint angles of the user is decided as follows.

$$\theta_{upij} = E_{upij}S_i^3 + F_{upij}S_i^2 + G_{upij}S_i + H_{upij} \tag{24}$$

Also, we decide the $\boldsymbol{\mu}_{upn}$ according to the following formula.

$$\boldsymbol{\mu}_{upn} = \frac{(h_u - h_B)\boldsymbol{\mu}_{Apn} + (h_A - h_u)\boldsymbol{\mu}_{Bpn}}{h_A - h_B} \tag{25}$$

where $\boldsymbol{\mu}_{upn}$, $\boldsymbol{\mu}_{Apn}$, and $\boldsymbol{\mu}_{Bpn}$ represent vector of sensor sample values of user, A, and B. The $\boldsymbol{\mu}_{upn}$ is used when using (4). Using a weighted average of hand size, each parameter for estimation can be determined.

D. Equivalency of Variance-Covariance Matrix

When using (4) to estimate hand motion, it is difficult to calculate the all parameters $\boldsymbol{\Sigma}_{pn}^{-1}$ directly for each user. So, we investigated equivalency of variance-covariance matrix between different users by using Box's M Test. First of all, we got the sensor values when each participant performed representative hand motions. Each representative hand motion is performed n times. Table VII shows an example of the sensor values at the time t in motion p. Next, the average of the sensor values $\overline{s_i}$ for finger i is obtained by the following formula.

TABLE VII. EXAMPLE OF SENSOR VALUE FOR MOTION p AT THE TIME t

trial	Thumb	Index	Middle	Ring	Little
1	s_{11}	s_{21}	s_{31}	s_{41}	s_{51}
2	s_{12}	s_{22}	s_{32}	s_{42}	s_{52}
3	s_{13}	s_{23}	s_{33}	s_{43}	s_{53}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
n	s_{1n}	s_{2n}	s_{3n}	s_{4n}	s_{5n}

$$\overline{s_i} = \frac{1}{n}\sum_{j=1}^{n} s_{ij} \tag{26}$$

At this time, covariance of finger x and y, represented as V_{xy}, is obtained by (27). And variance-covariance matrix $\boldsymbol{V}$ is defined as (28).

$$V_{xy} = \frac{1}{n}\sum_{k=1}^{n}(s_{xk} - \overline{s_x})(s_{yk} - \overline{s_y}) \tag{27}$$

$$\boldsymbol{V} = \begin{bmatrix} V_{11} & V_{12} & \dots & V_{15} \\ V_{21} & V_{22} & \dots & V_{25} \\ \vdots & \vdots & \ddots & \vdots \\ V_{51} & V_{52} & \dots & V_{55} \end{bmatrix} \tag{28}$$

Then we decide V' according to the following natural logarithm (29).

$$V' = \ln \frac{|\boldsymbol{V}_{AB}|^{\nu_1+\nu_2}}{|\boldsymbol{V}_A|^{\nu_1}|\boldsymbol{V}_B|^{\nu_2}} \tag{29}$$

$$\nu_1 = n_A - 1 \tag{30}$$

$$\nu_2 = n_B - 1 \tag{31}$$

where $\boldsymbol{V}_A$ and $\boldsymbol{V}_B$ represent mean variance-covariance matrix of participant A and B. The number of times n of participant A is different from B generally, each number is defined as n_A and n_B respectively. In this paper, each participant performs hand motion 10 times. And $\boldsymbol{V}_{AB}$ is the matrix obtained from the following formula.

$$\boldsymbol{V}_{AB} = \frac{\nu_1\boldsymbol{V}_A + \nu_2\boldsymbol{V}_B}{\nu_1 + \nu_2} \tag{32}$$

Also, we decide k according to the following formula.

$$k = 1 - \left(\frac{1}{\nu_1} + \frac{1}{\nu_2} - \frac{1}{\nu_1 + \nu_2}\right)\cdot\frac{2q^2 + 3q - 1}{6(q+1)} \tag{33}$$

where q represents the number of explanatory variables. Now q is number of Thumb, Index, Middle, Ring, and Little finger, 5. Finally, we obtain test statistic χ_0^2 from the following formula.

$$\chi_0^2 = kV' \tag{34}$$

The χ_0^2 follows chi-squared distribution. We describe the χ_0^2 of each motion/user in Table VIII. We decide significance level α as 0.001. The $\chi^2(\alpha = 0.001)$ is 37.70. So, if the χ_0^2 is smaller than 37.70, there is not significantly different in variance-covariance matripants as $\boldsymbol{\Sigma}_{pn}$. Finally we can obtain the finger joint angles of new user.

TABLE VIII. χ_0^2 OF EACH RESEARCH PARTICIPANT

	participant 1, 2	participant 2, 3	pariticpant 1, 3
Standard	22.44	28.64	28.84
Lateral Contact	29.34	36.22	20.87
Tripod	31.60	35.51	29.89
Parallel Ext	33.69	35.54	32.41

TABLE IX. ESTIMATED H_{size} OF PARTICIPANTS [cm]

	True H_{size}	Estimated H_{size}	Error
Participant 4	17.6	18.0	0.4
Participant 5	19.1	19.9	0.8

VIII. Experiment and Result for Hand Shape

We had an experiment to confirm the effectiveness of the method for hand shape.

A. Experiment Environment

We used 5DT data glove with representative hand motion set No.2 for two experiment systems, system A and system B. And two research participants 4 and 5 performed several hand motions.

1) System A: The system A estimates user's finger joint angles using same parameters for all users. These parameters were obtained by the hand of participant 2 because his hand size is mostly the same as average Japanese male's one.

2) System B: The system B estimates user's finger joint angles using parameters obtained by the user's own hand. User closes hand first, then each parameter is determined using H_{size}.

B. Estimation Results

Table IX shows estimated H_{size} of two participants. An estimation error of participant 4 is 0.37, and the error of participant 5 is 0.79. The method can estimate user's H_{size} almost correctly. We confirmed the effectiveness of the H_{size} estimation method described in Section VII-B.

Tables X to XIII show the average of the errors of the finger joint angles between estimated finger joint angles and obtained angles by CyberGlove. Besides, "Plastic bottle" represents the hand motion as same as in Section VII-A.

These results indicate that the estimation accuracy of the system B is better than the system A. We had Student's t-test to these averages of the errors of each finger joint angles. Tables XIV and XV show the differences of the estimation accuracy between the system A and B, and p-values obtained from Student's t-test. It is statistical significance if the $P(T \leq t)$ is smaller than 0.05. They show that there is statistical significance about the hand motion of which estimation accuracy were improved. There is not statistical significance about Parallel Ext, but the estimation accuracy was not improved. Totally the system B is better than the system A, it means calibrated parameters for each user is effectiveness, and hand size estimation is needed.

IX. Conclusion

In this paper, we described a useful method using a low-priced data-glove based on hand motion patterns. It estimates all finger joint angles using the data glove that sensors cover two joints of each finger, and also only the middle angle of each finger. A data glove is one of the major interfaces, which are used in the field of VR. It measures curvatures of fingers using bend sensor. However, in order to obtain accurate hand motions, it is necessary to use an expensive data glove, which has many sensors. On the other hand, there is a low cost data glove, which measures an angle for each finger through one sensor. It cannot get detailed data directly. Our method estimates plausible user hand motion patterns using each relation among angles of fingers during the operation of the low-cost glove first. Then, it estimates all finger joint angles by estimating the types of hand motion patterns from the correlation between each finger angle in the hand motion pattern. We assumed some representative hand motion patterns, and considered that other hand motions could be represented as synthetic motion of these. In the method for the glove whose sensors cover only the middle angle, the ratio of each representative motion pattern is calculated using Moore-Penrose pseudo-inverse matrix, and all finger angles are estimated using multiple regression analysis. The difference between users' hand shape was considered and confirmed using the glove whose sensors cover two joint angles. With the low priced data-glove being useful, it is expected that VR systems that target households will become more popular. In the future, we should reconsider the representative hand motion patterns because we removed Parallel Ext from our

TABLE X. JOINT ANGLE ERROR OF PARTICIPANT 4 IN SYSTEM A [DEGREE]

	Thumb	Index	Middle	Ring	Little	avg.
Standard	8.8	11.2	11.1	11.5	10.1	10.5
Lateral Contact	10.8	13.1	13.6	15.1	7.3	12.0
Tripod	18.6	10.6	13.5	11.5	17.5	14.4
Parallel Ext	10.4	13.4	8.8	9.0	10.3	10.4
Plastic bottle	15.2	10.7	15.3	20.2	9.9	14.3

TABLE XI. JOINT ANGLE ERROR OF PARTICIPANT 4 IN SYSTEM B [DEGREE]

	Thumb	Index	Middle	Ring	Little	avg.
Standard	6.5	6.3	3.6	15.0	18.4	10.0
Lateral Contact	12.0	11.7	11.4	11.4	8.7	11.0
Tripod	18.3	7.5	12.7	8.4	15.8	12.5
Parallel Ext	13.8	11.4	9.6	9.2	9.8	10.8
Plastic bottle	15.8	3.6	14.0	14.2	8.9	11.3

TABLE XII. JOINT ANGLE ERROR OF PARTICIPANT 5 IN SYSTEM A [DEGREE]

	Thumb	Index	Middle	Ring	Little	avg.
Standard	12.3	12.8	12.7	14.2	13.8	13.2
Lateral Contact	11.5	21.5	16.4	21.2	19.2	18.0
Tripod	10.2	8.2	12.8	22.9	17.6	14.3
Parallel Ext	24.0	9.2	4.3	7.6	13.6	11.7
Plastic bottle	23.2	13.6	16.2	31.0	20.8	21.0

TABLE XIII. JOINT ANGLE ERROR OF PARTICIPANT 5 IN SYSTEM B [DEGREE]

	Thumb	Index	Middle	Ring	Little	avg.
Standard	13.1	8.5	6.9	8.8	12.5	10.0
Lateral Contact	9.3	14.1	13.1	11.4	16.8	12.9
Tripod	9.4	7.7	18.8	19.0	17.5	14.5
Parallel Ext	13.0	8.8	16.0	10.8	13.5	12.4
Plastic bottle	26.1	10.3	20.8	13.4	11.0	16.3

TABLE XIV. DIFFERENCE BETWEEN SYSTEM A AND B OF PARTICIPANT 4

	participant 4	
	difference	$P(T \leq t)$
Standard	-0.6	3.3×10^{-2}
Lateral Contact	-1.0	2.7×10^{-2}
Tripod	-1.8	3.9×10^{-2}
Parallel Ext	+0.4	1.6×10^{-1}
Plastic bottle	-3.0	6.7×10^{-3}
average	-1.2	-

TABLE XV. DIFFERENCE BETWEEN SYSTEM A AND B OF PARTICIPANT 5

	participant 5	
	difference	$P(T \leq t)$
Standard	-3.2	3.4×10^{-2}
Lateral Contact	-5.0	1.7×10^{-2}
Tripod	+0.2	4.0×10^{-2}
Parallel Ext	+0.7	8.1×10^{-1}
Plastic bottle	-4.6	1.0×10^{-2}
average	-2.4	-

first research based on medical knowledge. We should also expand the target hand motion patterns to various ones that are not only grasping patterns.

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