A Data Adjustment Method of Low-priced Data-glove based on Representative Hand Motion Using Medical Knowledge

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ABSTRACT

A data glove is one of the interfaces which are used in the field of virtual reality. An expensive data glove has many sensors to capture a variety of human hand motion. On the other hand, low-priced data glove does not have enough sensors to capture hand motion directly. We have proposed the method to obtain all finger joint angles by estimating the pattern of user's hand motion from the sensor value. In our pilot experiment system, we assumed three representative hand motions as grasping behavior; grip, pinch, and nip. And we assumed that other hand motions can be represented by synthetic motion of them. However we have not discussed whether these hand motions are appropriate or not in order to express other hand motions. In this paper, we reconsider the representative hand motion using medical knowledge for more accurate finger joint angles.

Index Terms: Data-glove, hand motion estimation, finger joint angles estimation.

1 INTRODUCTION

In recent years, VR researches that targets to households have been attracted. It is preferable that an interface is small scale and low cost. In order to obtain accurate hand motions, it is necessary to use a data glove which has many sensors, but it is expensive. On the other hand, there is a low cost data glove which measures an angle of a finger through one sensor. But it cannot get detailed data directly. We have proposed the method to get plausible user hand motions from the low-cost one. This method estimates the kind of hand motions using each relation among angles of fingers during operation. Then it estimates all finger angles using the correlation between each finger angle in the hand motion assumed in advance[1]. Specifically, we assume the representative hand motions as grasping behavior; grip for a cube/cylinder type object, nip for a thin object, and pinch for a small object held by a thumb and an index finger. And we calculate the ratio of each representative motion. Moreover estimating each finger angle using the result, we express any hand motions other than the representative hand motions. However we have not discussed whether these hand motions are appropriate or not in order to express a variety of other hand motions. Thus, we try to find better representative hand motions from the research on the classification of the holding object pattern[2].

2 DATA ADJUSTMENT FOR LOW-PRICED GLOVE

2.1 Method of Hand Motion Estimation

First we sampled the sensor values for each representative hand motions and conducted D'Agostino-Pearson test at the 5 % significance level concerning these, and there was no significant differences. So we suppose distribution of each sensor value follows normal distribution and each sensor value as feature amount in five dimensional feature amount space also follows multivariate normal distribution when representative hand motions were performed. 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.

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

Where $\boldsymbol{S}$ is the sensor value vector. $\boldsymbol{\mu}_{pn}$ and $\boldsymbol{\Sigma}_{pn}$ represent mean vector of sensor values, variance covariance matrix of point n (an integer satisfying $1 \leq n \leq 25$) in representative hand motion p. Then if the sensor values are obtained actually from the glove, we select the maximum value according to the following formula.

$$L_p = \max_n \left\{L_{pn}\left(\boldsymbol{S} : \boldsymbol{\mu}_{pn}, \boldsymbol{\Sigma}_{pn}\right)\right\} \quad (2)$$

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

$$r_p = \frac{L_p}{\sum_{p=1}^{2} L_p} \quad (3)$$

2.2 Method of Finger Angles Determination

We calculate the weighted average of finger joint angles in each hand motion using finger joint angle equations obtained by experiment that utilize the ratio r_p as weighting factor to estimate the finger joint angles of the user.

$$\theta_{i1} = \frac{2}{3}\theta_{i2} \quad (4)$$

$$\theta_{i2} = E_{pi2}S_i^3 + F_{pi2}S_i^2 + G_{pi2}S_i + H_{pi2} \quad (5)$$

$$\theta_{i3} = E_{pi3}S_i^3 + F_{pi3}S_i^2 + G_{pi3}S_i + H_{pi3} \quad (6)$$

Where θ_{i1}, θ_{i2} and θ_{i3} express the DIP, PIP and MP joint angle of the finger i. S_i is sensor value of finger i. And E_{pij}, F_{pij}, G_{pij} and H_{pij} are constant for the motion p obtained by pre-experiment.

3 RECONSIDER REPRESENTATIVE HAND MOTIONS

3.1 Candidate Selection

We had set the three representative hand motions as grip, pinch and nip. In the following, we reconsider them through the research on the grasping behavior of human hand[2]. 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 (Fig. 1). 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 (Immersion CyberTouch). It was also confirmed that Parallel Flex and Circular Flex can be represented in a part of Standard (Fig. 2), and Phalangeal Ext can be represented in a part of Lateral Contact. Therefore we selected 7 motions as representative ones of candidate No.1.

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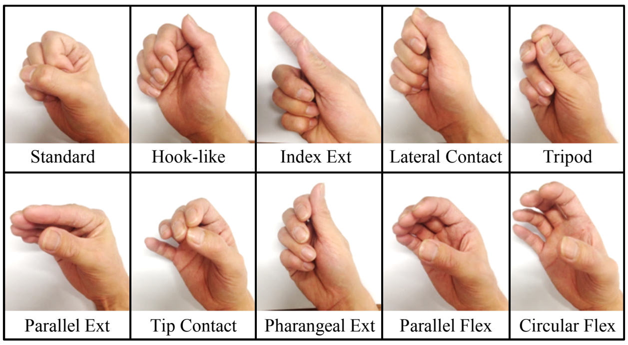

Figure 1: Hand Motions

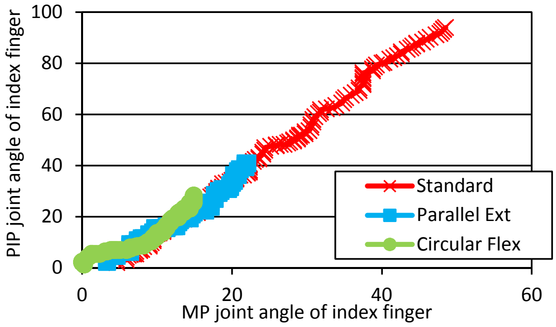

Figure 2: Example of MP and PIP Joint Angle of Index Finger

3.2 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, 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 (Fig. 3). 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 (Fig. 4), and obtained candidate No.3.

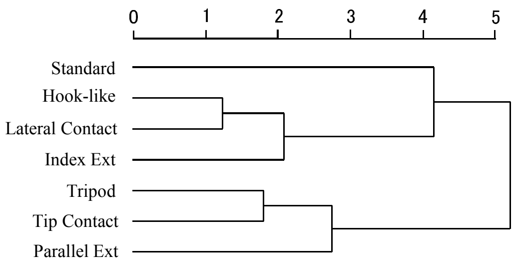

Figure 3: Dendrogram of the Candidata 1

4 Experiment and Conclusion

We constructed experiment system for the three candidates using the 5DT Data Glove 5 Ultra which has a bend sensor for each finger. It draws CG image based on the obtained finger joint angles (Fig. 5). 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[1]. Table 1 shows the average of the errors of DIP, PIP and MP between estimated finger joint angles and obtained angles by CyberTouch. The input data is Tripod motion for candidate 1 and 2, and MC_2 for candidate 3. Table 2 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. As a future work, we should decide the parameters as E_{pij} to H_{pij} of equation 5 and 6 for each user's hand shape, length and thickness.

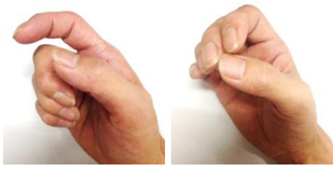

Figure 4: Average Hand Motions (left: MC_2, right: MC_3)

Figure 5: Appearance of Experiment System

Table 1: 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 2: 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

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