A Decision Method of a Placement of Tactile Sensors for Manipulation Task Recognition

Kazuya Matsuo, Kouji Murakami, Tsutomu Hasegawa and Ryo Kurazume

***Abstract*— This paper describes a decision method of a placement of tactile elements for manipulation task recognition. Based on the mutual information of the manipulation tasks and tactile information, an effective placement of tactile elements on a sensing glove is determined. Although the effective placement consists of a small number of tactile elements, it has recognition performance as high as that of many tactile elements. The effective placement of tactile elements decided by the method has been evaluated through experiments of recognizing the grasp types from grasp taxonomy defined by Kamakura [1].**

I. Introduction

A multi-jointed multi-fingered robotic hand [2] is a potentially dexterous hand like a human hand [3]. However, it is very difficult for us to manually and directly write down a motion program of multi-fingers moving synchronously and cooperatively to execute a task. Teaching-by-showing is an alternative approach: a motion of human fingers is measured and recognized, then it is somehow transformed into a motion program of a robotic hand. There are two approaches to Teaching-by-showing: direct mapping and symbolic programming.

There are generally many differences of structure between a human hand and a robotic hand: number of fingers, number of joints, disposition of fingers and so on. Therefore, it is not straightforward to utilize the data obtained by human workers in Teaching-by-Showing methods. Direct mapping of joint angle trajectories of the human hand onto the robotic hand will not execute the same manipulation task. Another method is to generate joint angle trajectories of the robotic hand from the fingertip trajectories of the human hand in the Cartesian coordinate system by solving inverse kinematics of the robotic hand. This may easily fail in keeping stable grasp of an object because possible direction and magnitude of the exerted force are not suitable due to the difference of the finger configuration even if the fingertip of the robotic hand is the same position as that of the human hand. The force control is required in order to overcome error in human motion measurement. Moreover, some joints may go over the limits of rotation angles. Wang et al. proposed a method of modifying fingertip positions of the robot according to the limits of rotation angles when the fingertip trajectories of the human hand was transformed and processed [4].

K. Matsuo is with Graduate School of Information Science and Electrical Engineering, Kyushu University, 744 Motooka, Nishi-Ku, Fukuoka 819-0395 JAPAN matsuo@irvs.is.kyushu-u.ac.jp

K. Murakami, T. Hasegawa and R. Kurazume are with Graduate Faculty of Information Science and Electrical Engineering, Kyushu University, 744 Motooka, Nishi-Ku, Fukuoka 819-0395 JAPAN {mkouji, hasegawa, kurazume}@irvs.is.kyushu-u.ac.jp

A task program for the robotic hand would be autonomously generated, if the actual task being executed by a human is recognized from the motion data of a human hand obtained through Teaching-by-Showing process. Related work on human motion recognition has been reported in [5][6][7][8][9][10][11]: the continuous human motion is segmented [1][12][13], recognized, and symbolized according to the meaning of the particular motion in the context of the task. A manipulation task by the human hand is represented by a sequence of symbols each representing particular manipulation. Adequately abstracted symbols enable to develop corresponding motion primitives feasible by a robot hand. Then the robot system would autonomously be able to perform various tasks by executing a sequence of corresponding motion primitives when a sequence of symbolic descriptions of a task performed by a human is given.

Joint angle trajectories of a human hand are usually used for manipulation task recognition. However, we may easily fail in recognition due to the large variation of the joint angle trajectories when a subject or an object shape is changed. Therefore, contact information between a hand and an object is often used for improving the recognition performance of manipulation tasks [10][11]. Seki et al. developed a grasping pressure distribution sensor with high flexibility in order to measure contact information between a hand and an object [14].

A placement of tactile elements is important when we recognize manipulation tasks by using contact information. Too many elements would obstruct the human from manipulation tasks. In addition, it takes the trouble to install many elements on a tactile sensing glove.

The objective of this work is development of a mathematical decision method of an effective placement of tactile elements for manipulation task recognition. Although the effective placement consists of a small number of tactile elements, it has the recognition performance as high as that of many tactile elements. Thus far, placements of tactile elements have been decided empirically in the previous work.

The remainder of this paper is organized as follows. A decision method of the effective placement of tactile elements for manipulation task recognition is proposed in Section II. Section III describes measurement devices for obtaining the contact information and the joint angle trajectories. Section IV shows experiments of recognizing the grasp types from the grasp taxonomy defined by Kamakura (Fig.1). Section V is a conclusion of this paper.

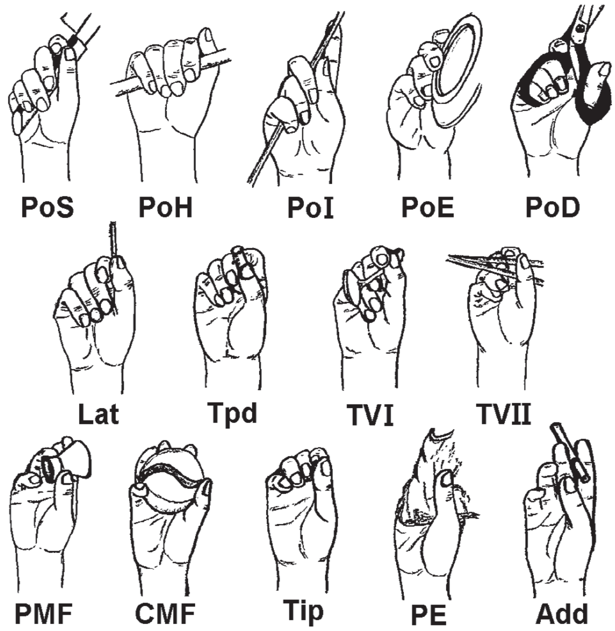


Fig. 1. Kamakura's taxonomy of prehension [1].

II. A Decision Method of a Placement of Tactile Elements

We propose a decision method of a placement of tactile elements. Firstly, a human subject performs manipulation tasks and obtain contact information with the tactile elements installed on a glove. Then the decision method selects an effective placement of tactile elements by using the contact information.

The method selects an effective placement by using ID3 (Iterative Dichotomiser 3) [15]. ID3 is a kind of supervised learning algorithm. Based on Occam's razor, ID3 constructs a small decision tree. ID3 calculates information gain of each input. Then ID3 makes a decision node labeled by the input whose information gain is maximum. Information gain of a input is the expected value of the information entropy to be given when we decide the value of the input. In other words, information gain is the mutual information of the outputs and each input. It is expressed as:

$$\begin{aligned} gain(x_i) &= H(C) - H(C \mid x_i) \\ H(C) &= -\sum_{y \in Y} p_y(C) log p_y(C) \\ H(C \mid x_i) &= -\sum_{j=1}^{n} \frac{|C_{ij}|}{|C|} \sum_{y \in Y} p_y(C_{ij}) log p_y(C_{ij}) \\ X_i &= \{v_j \mid j = 1, \cdots, n\}, \end{aligned}$$

where x_i is an input, y is an output, C is a set of training data, X_i is the set of x_i, v_j is a value of x_i, n is the number of v_j, Y is the set of y, $gain(x_i)$ is the information gain of x_i, $H(C)$ is the information entropy of C, $p_y(C)$ is the probability of y in C, and C_{ij} is the subset of C in the case of $x_i = v_j$.

The algorithm of ID3 is explained as follows.

(1) Create a root node 'N' for a tree.
(2) If all the elements of C give the same output 'y' then let N be a terminal node labeled by y, and end.
(3) Calculate information gain of each input 'x_i'.
(4) Select 'x_k' from the inputs so that the information gain of 'x_k' be maximized.
(5) Let N be a decision node labeled by x_k, and create child nodes 'N_j'.
(6) For each child node, $N_j \to N$, $C_{kj} \to C$. go to (2).

The proposed method constructs a decision tree by using ID3, where the inputs are the tactile elements. The outputs are the labels of the recognized manipulation tasks. The set of training data consists of the contact information through the demonstrations of the manipulation tasks. The method decides an effective placement for recognizing the manipulation tasks by using the tactile elements as the labels for the decision nodes of the tree.

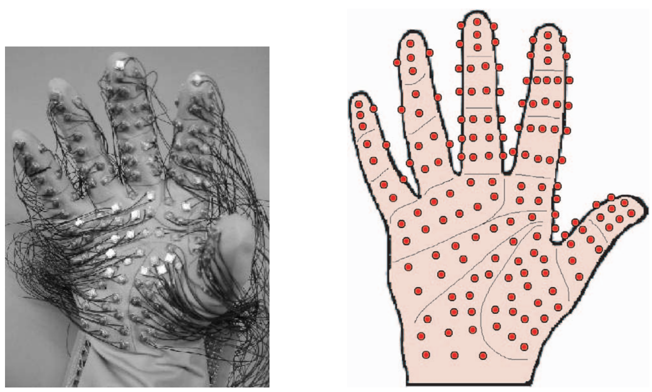
III. Measurement Devices

We use two kinds of sensors for measuring a human hand motion. They are a tactile sensing glove we designed and a data glove.

A. Contact Information

To measure positions of contact points between a hand and a grasped object, we designed a tactile sensing glove. 160 switches (EVQPLDA15 1.0: Matsushita Electric Industrial Corporation) are installed on it. Its appearance and the 160-switch placement are shown in Fig.2. The placement of the 160 switches is showm as the circles in Fig.2 (b). Circles in the outside of the contour of the hand indicate switches distributed on the sides of fingers.

The alternative switch is used. It outputs binary data of 'ON' or 'OFF'. Its thickness is $0.8mm$, and its shape is a square whose side is $5mm$. The thickness of its pushed part is $0.4mm$, and the shape of the pushed part is a circle whose diameter is $3.2mm$. When more than 1.0[N] force is exerted on the pushed part, the switch outputs the value of 'ON'. Contact information is 160 dimensional binary data provided from the 160 switches of the tactile sensing glove.



(a) (b)

Fig. 2. (a) Appearance of tactile sensing glove with 160 switches. (b) The 160-switch placement.

B. Joint-angle Information

We use a Cyber Glove (CG1802-R: Immersion Corporation) as an input device for measuring joint angles of a human hand. Its appearance and specifications are shown in Fig.3 and TABLE I respectively. The Cyber Glove has capability to measure angles of eighteen joints of a human hand. In order to recognize a manipulation task, we use angles of sixteen joints except two joints of a wrist. The positions of sixteen joints are shown in Fig.4. The thumb's proximal joint has two DOFs. The other fifteen joints have one DOF. Joint-angle information is 16 dimensional vector provided from the Cyber Glove.

Fig. 3. Appearance of Cyber Glove.

TABLE I

SPECIFICATIONS OF CYBER GLOVE (CG1802-R).

Number of Sensors	18
Sensor Resolution	0.5 degrees
Interface	RS-232
Maximum Data Rate	115.2 kbaud

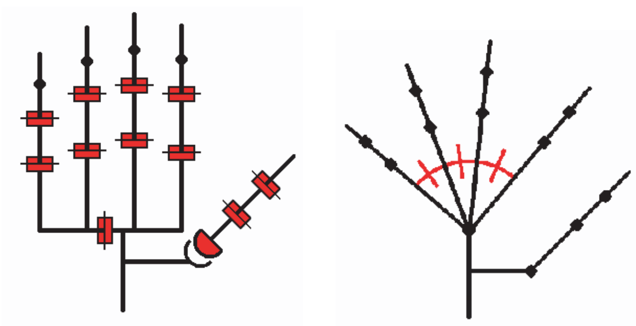


Fig. 4. Positions of measured joints of Cyber Glove.

IV. EXPERIMENTS

A. Manipulation Tasks

Our goal is to find an effective placement of tactile elements to recognize the manipulation tasks that are frequently executed in daily life, such as grasping a glass, holding a book, and so on. Kamakura, an occupational therapist, proposed a grasp taxonomy which consisted of 14 grasp types (Fig.1) used in daily life [1]. In this paper, we used the 14 grasp types defined by Kamakura as benchmarks for the sensor placement.

We collected three data sets. Each data set consists of contact information and joint-angle information of the 14 grasp types demonstrated by a subject. The subject wore the tactile sensing glove over the Cyber Glove when he performed the grasp types. He performed each grasp type with two different objects in the shape. He used daily life necessaries as the grasped objects (Fig.5). Mass of every object for the demonstrations is 0.9-334.9 [g]. He reproduced each grasp type 100 times in a random order. Three subjects (Subject-A, Subject-B and Subject-C) performed the demonstrations for three data sets. The three subjects are males whose ages are 23-32.

Fig. 5. Appearances of the grasped objects.

Although the thickness and the wiring of each glove might seem to interfere with the 14 grasp types, we confirmed through visual observation that the subjects performed the 14 grasp types. Appearances of Kamakura's grasp types with the Cyber Glove and the tactile sensing glove are shown in Fig.6. All these objects for the demonstrations are light in weight. Therefore, the influence of the weight on sensor reading is negligible.

B. Placement Selection Results

The method selected a placement of tactile elements to recognize the 14 grasp types based on contact information of each data set. The selected placement of each subject is shown in Fig.7. The placements consist of 27-33 tactile elements.

C. Evaluation of the Selected Placements of Tactile Elements

The selected placements were evaluated through experiments of recognizing the 14 grasp types. We investigated recognition performance of the selected placements by using LogitBoost algorithm [16]. The algorithm was implemented using Weka [17] which is a collection of machine learning

Fig. 6. Appearances of Kamakura's grasp types with the Cyber Glove and the tactile sensing glove.

algorithms for data mining tasks. Decision stumps were applied as weak learners of the algorithm. The number of the weak learners was 100. Weka's default values were applied as parameters of the learning process. For comparison, we prepared seven different data sets as inputs of the algorithm. We evaluated the selected placements through four-fold cross validation on the seven data sets. The seven data sets are as follows.

① Contact information from all the elements (All-Co.).

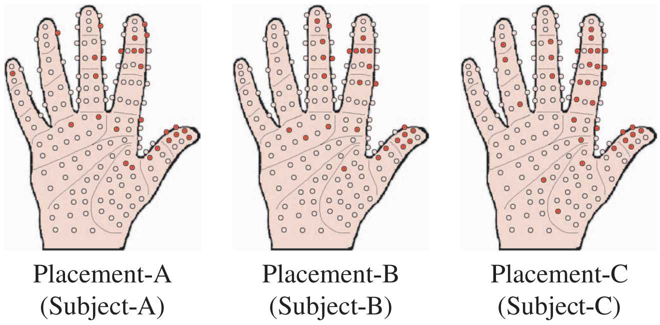


Fig. 7. Effective placements of tactile elements for recognizing the 14 grasp types.

② Contact information from the selected elements (Key-Co.).

③ Contact information from all the rest of elements except the selected ones (NKey-Co.).

④ Joint-angle information and contact information from all the elements (An. + All-Co.).

⑤ Joint-angle information and contact information from the selected elements (An. + Key-Co.).

⑥ Joint-angle information and contact information from all the rest of elements except the selected ones (An. + NKey-Co.).

⑦ Joint-angle information without contact information (An.).

The recognition rates are shown in TABLE II. The recognition rate is defined as the ratio of the number of successful data to the number of input data.

TABLE II
RECOGNITION RATES [%] (THE SEVEN DATA SETS).

Subjects	A	B	C
① All-Co.	88.4	90.0	88.8
② Key-Co.	88.4	90.0	88.7
③ NKey-Co.	64.6	67.9	69.1
④ An. + All-Co.	100	100	99.9
⑤ An. + Key-Co.	100	100	99.9
⑥ An. + NKey-Co.	91.4	100	89.9
⑦ An.	90.0	100	84.9

The results of the evaluation is summarized as followings.

- From input data of ①④⑦:
  Although the recognition rates by using joint-angle information without contact information⑦ or contact information from all the elements① are about 90%, the recognition rates by using both the information④ are approximately 100%. The sensor fusion improves the recognition performance.
- From input data of ①②③:
  The recognition rates by using contact information from the selected elements② are as high as those by using contact information from all the 160 elements①. On the other hand the recognition rates by using contact information from all the rest of elements except the selected ones③ deteriorate. Although the selected placements consist of small numbers of tactile elements, they have recognition performance as high as that of many tactile elements.
- From input data of ④⑤⑥:
  Similar result is shown when contact information is integrated with joint-angle information④⑤⑥.

D. Generality of the Selected Placements of Tactile Elements

In order to evaluate generality of the selected placement, we investigated one subject's recognition rate by using another subject's placement. TABLE III shows the recognition rates where one subject's evaluation data② are recognized by using another's placement.

TABLE III
RECOGNITION RATES [%]:
ONE SUBJECT'S EVALUATION DATA (COLUMN) ARE RECOGNIZED BY USING ANOTHER SUBJECT'S PLACEMENT (ROW).

placements \ evaluation data	A	B	C
Placement-A	88.4	89.6	81.6
Placement-B	85.4	90.0	87.7
Placement-C	85.6	89.6	88.7

The recognition rates of each subject's evaluation data by using the other subjects' placements are lower than that by using the same subject's placement by 0.4-7.1 [%].

E. Comparison of the effective placements of tactile elements and locations of human mechanoreceptive units

We compare the selected placements of tactile elements with locations of mechanoreceptive units in the human hand. When densities of two types of the mechanoreceptive units (FAI and SAI units) are high, spatial resolution capacity in the human hand is large [18]. Therefore, we compare the selected placements (Fig.7) with the locations of the FAI and SAI units [19] (Fig.8). It is interesting that the selected placements are similar to the locations of the two types of the mechanoreceptive units.

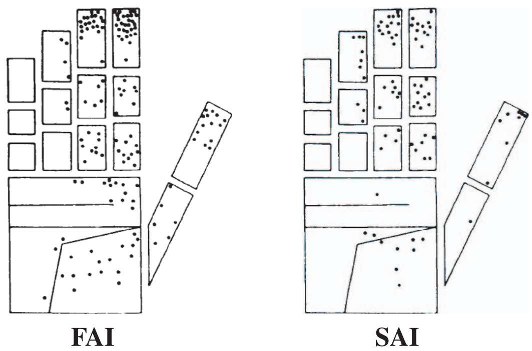


Fig. 8. Locations of the receptive field centers of two types of mechanoreceptive units (FAI and SAI units) [19].

V. CONCLUSIONS

We have developed a decision method of a placement of tactile elements for manipulation task recognition. LogitBoost algorithm recognized 14 grasp types from grasp taxonomy defined by Kamakura based on the placements of tactile elements decided by the method. Although the placements consist of only 27-33 tactile elements, they have recognition performance as high as that of a placement which consists of 160 tactile elements.

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