A Decision Method of Placement of Tactile Elements for Recognizing Tasks Executed by a Human Hand

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Abstract— **This paper describes a decision method of placement of tactile elements for manual task recognition. Based on the mutual information of the manual 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 a lot of 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.**

I. Introduction

A multi-jointed multi-fingered robotic hand [1] is a potentially dexterous hand like a human hand. 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. This paper proposes a decision method of placement of tactile elements for recognizing manual tasks executed by a human hand.

There are usually many differences of structure between a human hand and a robotic hand: number of fingers, number of joints, length of a finger link and so on. Therefore it is not straightforward to utilize the data obtained in Teaching-by-Showing by a human worker. Direct mapping of joint angle trajectories of the human hand onto the robotic hand will not execute the same manual 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 operating force differs due to the difference of the finger configuration even if the fingertip position is the same. Moreover, some joints may go over the limit of rotation. The force control is essential to overcome error in human motion measurement. Wang et al. proposed a method of modifying fingertip positions of the robot according to the limit of rotation when the fingertip trajectories of the human hand was transformed and processed [2].

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 in Teaching-by-Showing process. Related work on human motion recognition has been reported in [3][4][5][6][7][8][9]: the continuous human motion is segmented [10][11][12], recognized, and symbolized according to the meaning of the particular motion in the context of the task. A manual 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 recognizing manual tasks. However, we may fail in recognition due to the large changes of joint angle trajectories when a subject and an object shape are changed. In addition, we can not obtain contact information between a hand and an object from the joint angle trajectories only.

Contact information between a hand and an object is used for improving the recognition performance of manual tasks [8][9]. Placement of tactile elements is important when we recognize manual tasks by using contact information. Too many elements would obstruct the human from manual tasks. In addition, many tactile elements cost us a great effort for having them installed. Effective placement is required. Although the effective placement consists of a small number of tactile elements, it has the recognition performance as high as that of a lot of tactile elements. Thus far, the placement of tactile elements has been decided by human intuition in the previous work.

The remainder of this paper is organized as follows. A decision method of the effective placement of tactile elements for recognizing manual tasks 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.

II. A Decision Method of Placement of Tactile Elements

Firstly, we perform manual tasks and obtain contact information with tactile elements installed on a glove. Then we select an effective placement of tactile elements for recognizing the manual tasks based on the contact information (Fig.2).

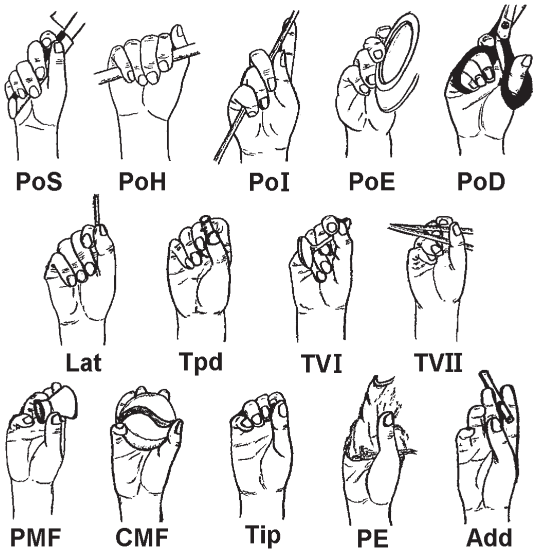


Fig. 1. Kamakura's taxonomy of prehension [10].

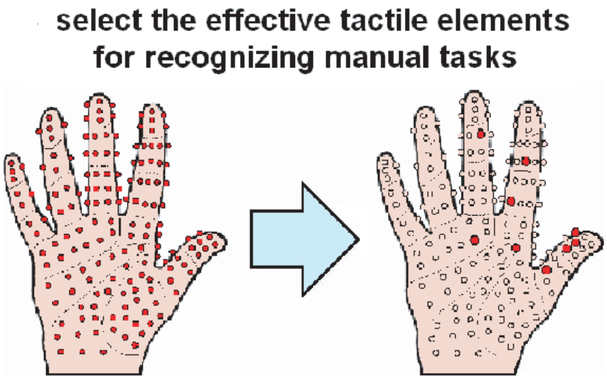


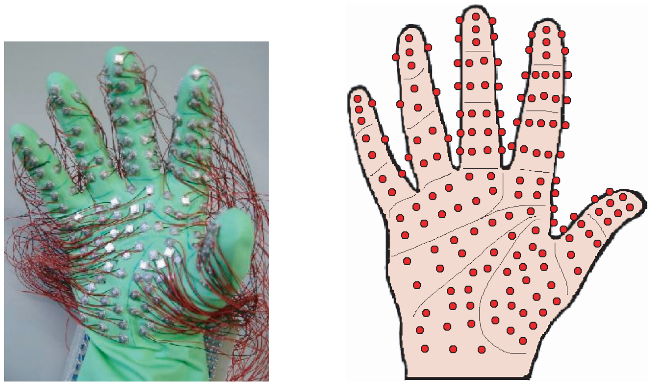
Fig. 2. Concept of the proposed method.

We select the effective placement based on ID3 (Iterative Dichotomiser 3) [13].

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 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 input, y is output, C is the set of training data, $gain(x_i)$ is information gain of x_i, $H(C)$ is 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 $x_i = v_j$.



(a) (b)

Fig. 3. (a) Appearance of tactile sensing glove with 160 switches. (b) 160-switch placement.

The algorithm of ID3 is explained as follows.

(1) Create a root node 'N' for the 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, $N_j \rightarrow N$, $C_{kj} \rightarrow C$. go to (2).

A small decision tree is constructed by ID3, where the inputs are the tactile elements, the outputs are identifies of the manual tasks, and training data are contact data when subjects performed the manual tasks. The effective placement for recognizing the manual tasks consists of the elements which are the decision attributes for the decision 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 obtain 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.3. The 160-switch placement is showm as the circles in Fig.3 (b). Circles at the outside of manual outline indicate switches installed 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 sides are 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.

Fig. 4. 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

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.4 and TABLE I respectively. The Cyber Glove has capability to measure angles of eighteen joints of a human hand. In order to recognize a manual task, we use angles of sixteen joints except two joints of a wrist. The positions of sixteen joints are shown in Fig.5. 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.

IV. EXPERIMENTS

A. Tasks for Experiments

Our goal is to recognize the manual tasks that are frequently executed in daily life, such as grasping a glass, holding a book, and so on. Kamakura proposed a grasp taxonomy which consisted of 14 grasp types (Fig.1) used in daily life. In this paper, we recognize 14 grasps defined by Kamakura.

We collected three data sets. Each data set consists of contact information and joint-angle information of the 14 grasps demonstrated by a subject. The subject wore the tactile sensing glove over the Cyber Glove when he performed the grasps. He performed each grasp with two different objects in the shape. He reproduced each grasp 100 times in a random order. Three subjects (Subject-A, Subject-B and Subject-C) performed the demonstrations for three data sets.

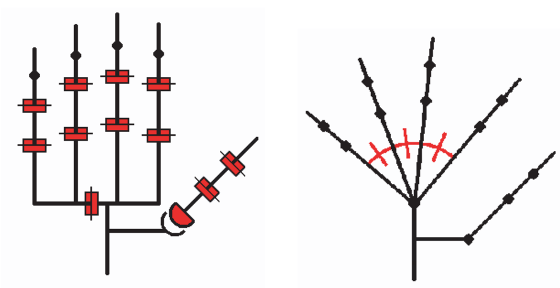
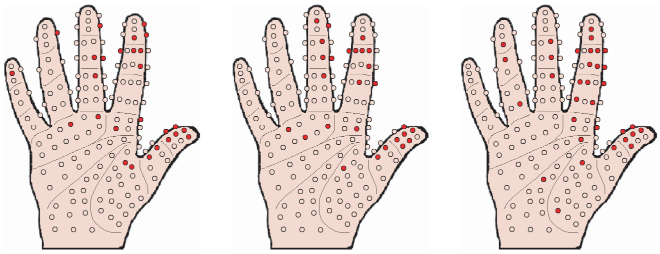


Fig. 5. Positions of measured joints of Cyber Glove.



Placement-A (Subject-A) Placement-B (Subject-B) Placement-C (Subject-C)

Fig. 6. Effective placement of tactile elements for recognizing 14 grasps.

B. Placement of Tactile Elements Selection Results

The proposed method selected a placement of tactile elements to recognize the 14 grasps based on contact information of each data set. The selected placement of each subject is shown in Fig.6. Each placement consists of 27-33 tactile elements.

C. Evaluation of the Selected Placement of Tactile Elements

The selected placements were evaluated through experiments of recognizing the 14 grasps. For comparison, we prepared seven kinds of inputs of each data set. The seven kinds of inputs are as follows.

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

We evaluated the selected placements by using four-fold cross validation on the seven kinds of inputs. We investigated recognition rates of AdaBoost algorithm [14] in which decision stumps were applied as weak learners. The algorithm was implemented using Weka [15] which is a collection of machine learning algorithms for data mining tasks. The number of weak learners was 100. Weka's default values were used as parameters of the algorithm. The recognition rates are shown in TABLE II. Recognition rate is defined as the ratio of the number of successful data to the number of input data.

The results of the evaluation is summarized as followings.

- From inputs 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

TABLE II
RECOGNITION RATE [%] (SEVEN KINDS OF INPUTS).

Subject	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

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

placement \ 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

recognition rates by using both the information④ are approximately 100%. The sensor fusion improves the recognition performance.

- From inputs 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 those of many tactile elements.
- From inputs of ④⑤⑥:
  Similar result is obtained when contact information is integrated with joint-angle information④⑤⑥.

D. Generality of the Selected Placements of Tactile Elements

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

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%.

V. CONCLUSIONS

We have presented a decision method of placement of tactile elements for recognizing manual tasks executed by a human hand. AdaBoost algorithm recognized 14 grasp types from grasp taxonomy defined by Kamakura based on the placements of tactile elements decided by the proposed method. Although the placements consist of only 27 or 33 tactile elements, they have recognition performance as high as that of the placement which consists of 160 tactile elements.

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