A Decision Method for Placement of Tactile Elements on a Sensor Glove for the Recognition of Grasp Types

Kouji Murakami, Kazuya Matsuo, Tsutomu Hasegawa, Ryo Kurazume

***Abstract*—We describe a decision method for effective placement of tactile elements for grasp type recognition. Not only does the placement decided by our method require a small number of tactile elements, it also achieves a recognition performance as high as placements consisting of many elements. The placement decided by the method is evaluated through experiments involving the recognition of grasp type from the two types of grasp taxonomy defined by Cutkosky and Kamakura. The proposed method is extended by applying a decision tree pruning. The pruning is useful for reducing the number of selected tactile elements without badly dropping the recognition rate.**

***Index Terms*—tactile sensor, grasp type recognition, human tactile receptor**

I. Introduction

A multi-jointed, multi-fingered robotic hand has the potential to grasp commonly used objects of various shapes [1][2][3][4][5][6]. However, selecting a grasp configuration to grasp an object stably is a difficult problem due to the huge number of possibilities. Even for a simple three-fingered robotic hand such as the Barrett Hand (Barrett Technology Inc.) [7], there are ten degrees of freedom that set its grasp configuration. A brute-force search of grasp configurations would still be intractable.

One approach to overcome this problem is based on grasp preshape [8][9]. A grasp preshape is defined as the finger configuration when a hand begins the closing process. The shape of an object and the task purpose determine the suitable grasp preshapes and thus limit the number of possible grasp configurations. However, this grasp preshape approach has following two problems.

- Modelization of a set of grasp preshapes
- Selection strategy of a grasp preshape

The particular shapes of the grasps by a human hand are used to model a set of preshapes for a robotic hand. Napier classified human hand shapes into a precision grasp and a power grasp [10]. In the power grasp, the object is grasped by the whole hand, including the fingers, thumb, and palm. In contrast, in the precision grasp, the object is grasped only by the fingertips. This classification was extended by considering the shape of an object and the task purpose. Kamakura, an occupational therapist, proposed a grasp taxonomy consisting of 14 hand shapes used in daily life [11]. This taxonomy is shown in Fig. 1. As shown in Fig. 2, Cutkosky proposed a grasp taxonomy consisting of 16 hand shapes used by humans working with tools and metal parts [12]. These classified hand shapes are called *grasp types*. A set of grasp preshapes for a robotic hand is produced from these human grasp types. Miller et al. presented four grasp preshapes of the Barrett Hand, and each of them reproduced the power grasp or precision grasp [8]. By selecting the grasp preshape suitable for the shape of an object, each object was successfully grasped. Ekvall et al. created eight grasp preshapes of the Barrett Hand and Robonaut Hand, and reproduced ten grasp types from Cutkosky's grasp taxonomy [9]. Experiments have shown that, by selecting the proper grasp preshape, an object can be grasped robustly against the error of the position measurement of the object and the error of the object shape model.

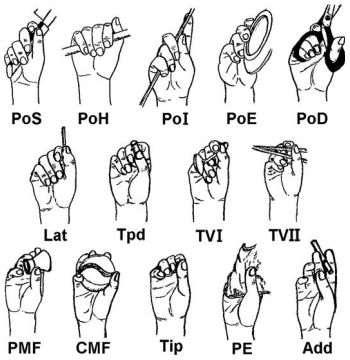

Fig. 1. Kamakura's taxonomy of prehension [11].

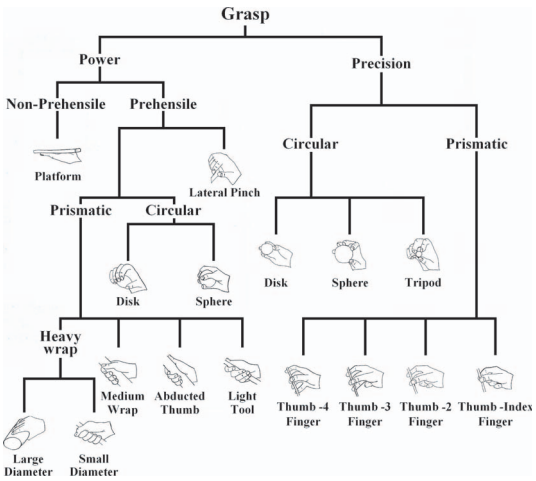

Fig. 2. Cutkosky's taxonomy of prehension [12].

Appropriate grasp preshapes differ according to the requirements of its task and situation, even if grasping the same object. For example, the grasp preshape suitable for grasping the handle of a cup is different from the grasp preshape suitable for grasping the brim of the cup. In previous work, grasp preshapes were selected by a human operator. Selection of a grasp preshape by a human depends on that person's work experience and work knowledge, such as knowledge of the shape of an object and the purpose of a task. It is difficult for a robotic hand system to automatically select a grasp preshape suitable for a task situation.

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The recognition of human grasp types is useful for the planning of grasp preshape in a robotic hand system. A data glove and a vision camera are often used for the recognition of human grasp types. In one method, the final joint angles of a human hand are measured with a data glove when the grasp is set [13][14][15][16][17]. Another method is to measure the locations of visual markers distributed on a human hand with a vision camera [18]. Electromyographic signals of a human arm is also used for the recogntion [19]. The recognition of grasp types has been demonstrated by applying these methods. However, whether the hand contacts an object cannot be decided from the information measured by a data glove and a vision camera. Therefore, contact information between a hand and a grasped object is being used to advance the recognition of grasp types [15][16]. The recognition performance depends on the placement of tactile elements distributed on a measurement device. Previous research has empirically determined the placement of tactile elements.

The purpose of this paper is to investigate the relationship between the number/placement of tactile elements and its recognition rate, and to develop a method for optimizing the number/placement of tactile element. Therefore we propose a mathematical decision method for effective placement of tactile elements for the recognition of grasp types from the two types of grasp taxonomy defined by Kamakura and Cutkosky. Even though the placement decided by our method requires only a small number of tactile elements, the recognition performance is as high as placements consisting of many elements. The selection of effective placement is useful for designing devices to measure the contact information. Preliminary results of this work were presented in [20].

Our goal is to develop a method to select the proper grasp preshape of a robotic hand in a grasping task. In a programming-by-demonstration approach [21][22][23], a proper grasp preshape of the robotic hand will be autonomously selected from the recognized human grasp type. The proposed mathematical decision method is useful in that recognition process.

II. Decision Method for the Placement of Tactile Elements

As stated above, we propose a mathematical decision method for the placement of tactile elements. First, a human subject performs types of grasps, and contact information is obtained from the tactile elements installed uniformly on a glove. The decision method then selects effective placement of the tactile elements using the contact information.

The method applies ID3 (Iterative Dichotomiser 3) [24], which is a kind of supervised learning algorithm. Based on Occam's razor, ID3 constructs a small decision tree, calculates the information gain of each input and then makes a decision node labeled by the input having the maximum information gain. The information gain of an input is the expected value of the information entropy given when we decide the value of the input. In other words, the information gain is the mutual information of the outputs and each input, and is expressed as follows:

$$
\begin{aligned}
gain(x_i) &= H(C) - H(C \mid x_i), \\
H(C) &= -\sum_{y_j \in Y} p_{y_j}(C) log p_{y_j}(C), \\
H(C \mid x_i) &= -\sum_{k=1}^{L} \frac{|C_{ik}|}{|C|} \sum_{y_j \in Y} p_{y_j}(C_{ik}) log p_{y_j}(C_{ik}), \\
x_i &= v_k \quad (k = 1, \cdots, L),
\end{aligned}
$$

where $gain(x_i)$ is the information gain of x_i, x_i is an input, y_j is an output, C is a set of training data, v_k is a value of x_i, L is the number of v_k, Y is the set of y_j, $H(C)$ is the information entropy of C, $p_{y_j}(C)$ is the probability of y_j in C, and C_{ik} is a subset of C in the case of $x_i = v_k$.

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, then let N be a terminal node labeled by y_j, and end.
(3) Calculate the information gain of each input x_i.
(4) Select x_{max} from the inputs so that the information gain of x_{max} is maximized.
(5) Let N be a decision node labeled by x_{max} and create child nodes N'.
(6) For each child node, $N' \rightarrow N$, $C_{max,k} \rightarrow C$, go to (2).

In the decision tree made by ID3, inputs x_i are the tactile elements and outputs y_j are the labels of the recognized grasp types. The set of training data C consists of contact information obtained through demonstration of the grasp types. The contact information is the set of the outputs of the tactile elements. The contact information is obtained through reproduction of the grasp types (see Fig. 3). The proposed 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 (see Fig. 4).

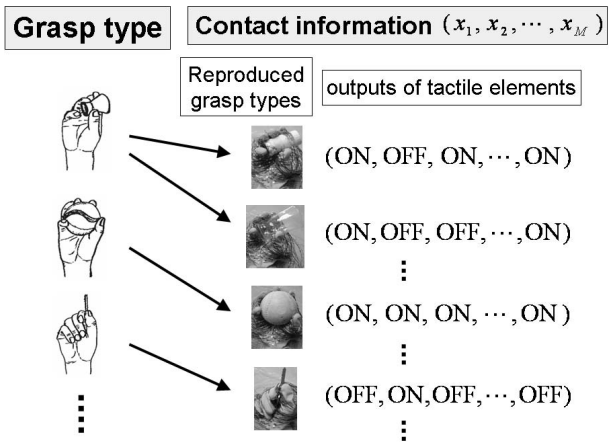


Fig. 3. Contact information measured by reproduction of the grasp types.

A decision tree pruning is effective for reducing the number of selected tactile elements in the proposed method. Pruning makes the decision tree smaller by removing decision nodes that are less helpful for the recognition. A simple pruning method is implemented in Section IV-A4).

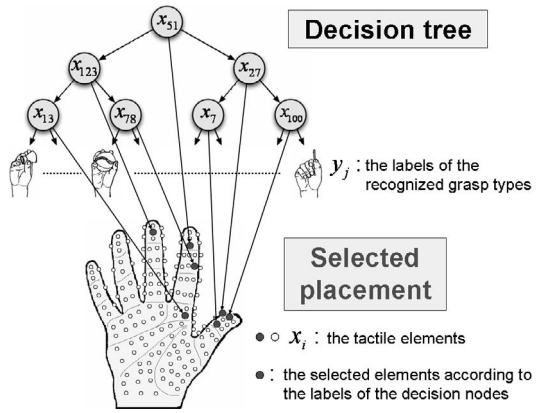


Fig. 4. Selected placement for recognizing the grasp types by using the tactile elements as the labels for the decision nodes of the tree.

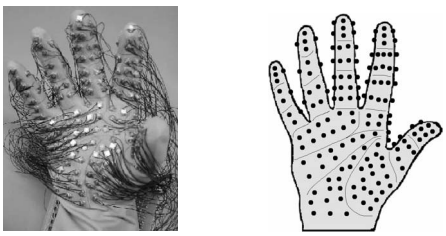
III. Measurement Devices

We use two different types of sensors to measure human hand motion. They are a tactile sensing glove designed by the authors and a cyber glove (Immersion Corporation) for measuring joint angles.

A. Contact Information

To measure the locations of contact points between a human hand and a grasped object, we designed a tactile sensing glove. A total of 160 switches (EVQPLDA15 1.0: Matsushita Electric Industrial Corporation) are installed on the glove. A photograph of the glove is shown in Fig. 5 (a). The placement of the 160 switches is represented by circles in Fig. 5 (b). The circles outside the contour of the hand indicate switches distributed on the sides of the fingers.

Alternative switches, which output binary data (ON or OFF) are used for the glove. The circular contact mechanism of each switch is 3.2 mm in diameter and is 0.4 mm in thickness. When a force of more than 1.0 [N] is exerted on the contact mechanism, the switch outputs the value of ON. The contact information becomes 160-dimensional binary data provided from the 160 switches of the tactile sensing glove.



(a) (b)

Fig. 5. (a) Photograph of the tactile sensing glove with 160 switches, (b) Placement of the 160 switches.

B. Joint-angle Information

Several sensing devices for measuring joint angles have been presented [25]. We use a Cyber Glove (CG1802-R: Immersion Corporation) as an input device for measuring the joint angles of a human hand. The specifications of the glove are shown in TABLE I. The Cyber Glove can measure the angles of the eighteen joints of a human hand. To recognize a manipulation task, we use the angles of sixteen joints, excluding the two wrist joints. The joint-angle information is in the form of a 16-dimensional vector provided by the Cyber Glove.

TABLE I
Specifications of the Cyber Glove (CG1802-R).

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

IV. Experiments

A. Recognition of the Grasp Types Defined by Kamakura

One goal of the present study is to find an effective placement of tactile elements to recognize the grasp types that are frequently executed in daily life, such as grasping a glass or holding a book. As shown in Fig. 1, Kamakura proposed a grasp taxonomy consisting of 14 grasp types used in daily life [11]. In the present paper, we used the 14 grasp types defined by Kamakura as benchmarks for the placement of tactile elements.

We collected three data sets, each of which consists of the contact information and joint-angle information of the Kamakura's 14 grasp types demonstrated by three human subjects (Subject-A, Subject-B and Subject-C). The three subjects were males of age 23 to 32 years. The subject wore the tactile sensing glove over the Cyber Glove while performing each grasp type with objects of different volumes. Two objects of different volumes are used at every grasp type. The total number of the grasped objects is twenty-eight. The objects are commonly encountered in daily life. The weight of the objects ranged from 0.9 [g] to 334.9 [g]. Each subject reproduced each grasp type 100 times in random order, thus generating three data sets. Although the thickness and wiring of each glove may appear to be cumbersome, we confirmed through visual observation that the subjects adequately performed the 14 grasp types. Photographs of Kamakura's grasp types using the Cyber Glove and the tactile sensing glove are shown in Fig. 6.

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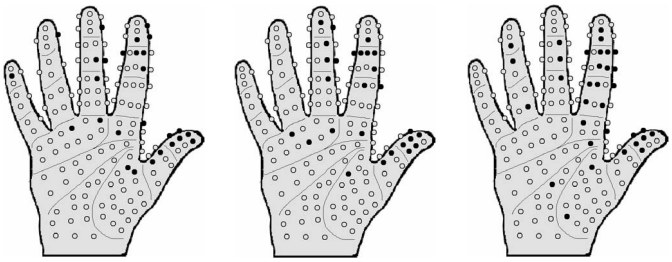
Fig. 6. Photographs of several Kamakura's grasp types.

1) Placement Selection Results (Kamakura): The proposed decision method was used to determine the placement of tactile elements to recognize the 14 grasp types based on the contact information of each data set. The selected placements for each

subject are shown in Fig. 7. The placements consist of 27, 27 and 33 tactile elements for Subject-A, Subject-B and Subject-C, respectively. The densities of the selected elements on the thumb and the index finger are higher than those on the other fingers and the palm.



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

Fig. 7. Effective placements of tactile elements for the recognition of Kamakura's grasp types.

2) Evaluation of the Selected Placements of Tactile Elements (Kamakura): The selected placements were evaluated through experiments involving the recognition of the 14 grasp types. We investigated the recognition performance of the selected placements using the LogitBoost algorithm [26]. The algorithm was implemented using Weka [27], which is a collection of machine learning algorithms for data mining tasks. Decision stumps were applied as weak learners of the algorithm. The number of 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 validations on the seven data sets. The seven data sets are as follows.

- I Joint-angle information and contact information from all of the elements (Angle + All-Co).
- II Joint-angle information and contact information from the selected elements (Angle + Sel-Co).
- III Joint-angle information and contact information from the non-selected elements (Angle + NoSel-Co.).
- IV Joint-angle information without contact information (Angle).
- V Contact information from all of the elements (All-Co).
- VI Contact information from the selected elements (Sel-Co).
- VII Contact information from the non-selected elements (NoSel-Co).

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

The results of the evaluation (TABLE II) are summarized as follows.

- From the input data of I, IV, and V:
  Although the recognition rates using only the joint-angle information IV or the contact information V are approximately 90%, the recognition rates using both types of information I are approximately 100%. Thus, sensor fusion improves the recognition performance.
- From the input data of I, II, and III:
  The recognition rates using the selected elements and the angles II are approximately 100%, which are as high as those using the 160 elements and angles I. In contrast, the recognition rates using the non-selected elements and angles III are reduced to approximately 90%. Although the selected placements consist of small numbers of tactile elements, they have recognition performances that are as high as those for many elements.
- From the input data of V, VI, and VII:
  Similar results are obtained when the contact information V, VI, and VII is used without joint-angle information.

TABLE II
RECOGNITION RATES [%] (THE SEVEN COMPOSITIONS OF INPUTS, KAMAKURA).

Input data				Recognition rates [%]		
No.	Sel-Co	NoSel-Co	Angle	SubjectA	SubjectB	SubjectC
I	√	√	√	100	100	99.9
II	√		√	100	100	99.9
III		√	√	91.4	100	89.9
IV			√	90.0	100	84.9
V	√	√		88.4	90.0	88.8
VI	√			88.4	90.0	88.7
VII		√		64.6	67.9	69.1

3) Generality of the Selected Placements of Tactile Elements (Kamakura): To evaluate the generality of the selected placements (Fig. 7), we investigated the recognition rate of one subject using the placement of another subject. TABLE III shows the recognition rates obtained when the evaluation data^{VI} of one subject are recognized using the placement of another subject. We use the input data of VI for this investigation.

TABLE III
RECOGNITION RATES [%]: THE EVALUATION DATA (COLUMN) OF ONE SUBJECT ARE RECOGNIZED BY USING THE PLACEMENT (ROW) OF ANOTHER SUBJECT, KAMAKURA.

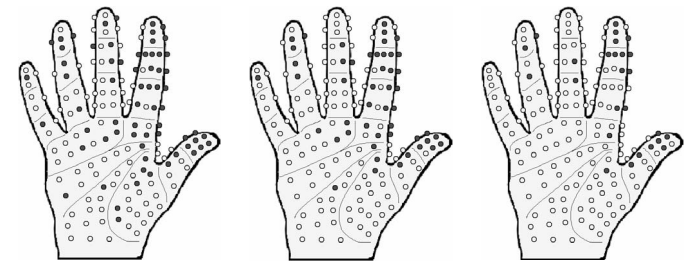
Placement \ Evaluation data	A	B	C	average
Placement-A	88.4	89.6	81.6	86.5
Placement-B	85.4	90.0	87.7	87.7
Placement-C	85.6	89.6	88.7	88.0

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

4) Decision Tree Pruning (Kamakura): We reduced the number of selected elements by applying pruning, and investigated the relationship between the recognition rates and the reduced number of the selected tactile elements. A simple pruning method was implemented by applying the following modification to the algorithm in section II. At the step (2) of the algorithm, if the number of the elements of C is less than the specified number S, then let N be a terminal node, and end.

We used the set of contact information of the three subjects

as the input data of the extended method for this investigation. The extended method was used to determine the placement of tactile elements to recognize the Kamakura's 14 grasp types. The number of the selected elements was 66 without pruning (Fig. 8(a)). In contrast, the number of the selected elements was 49 when the specified number S was 13 in pruning process (Fig. 8(b)). The number of the selected elements was 26 when the specified number S was 62 in pruning process (Fig. 8(c)). The selected placements of each case are shown in Fig. 8. The recognition rates are shown in TABLE IV. The number of the selected elements is reduced from 66 to 26 by pruning. In contrast, the recognition rate using the selected elements decreased by 0.9% to 88.1% by pruning. The recognition rate using the 26 elements selected by pruning is higher than the recognition rates using 27, 27, and 33 elements in TABLE III.



(a) without pruning (66 elements) (b) pruning I (49 elements) (c) pruning II (26 elements)

Fig. 8. Reduction of the number of selected tactile elements by pruning for the recognition of Kamakura's grasp types. (a) The selected placement without pruning. (b) pruning I: The selected placement with pruning (The specified number S is 13). (c) pruning II: The selected placement with pruning (The specified number S is 62).

TABLE IV
RECOGNITION RATES [%]: EVALUATION DATA (COLUMN) ARE RECOGNIZED BY USING THE PLACEMENTS SELECTED WITH PRUNING (ROW), KAMAKURA.

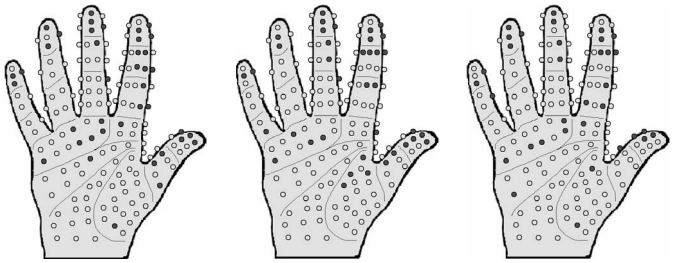
The number of selected elements	Subjects			average
	A	B	C	
160	88.4	90.0	88.8	89.1
66	88.3	90.0	88.8	89.0
49	88.2	90.0	88.8	89.0
26	86.6	89.6	88.0	88.1

B. Recognition of Grasp Types Defined by Cutkosky

We also used Cutkosky's grasp types as benchmarks for sensor placement. As shown in Fig. 2), Cutkosky proposed a grasp taxonomy consisting of 16 grasp types used by humans working with tools and metal parts [12]. The classified grasp types are used for implementing a grasping motion and designing a robotic hand.

We conducted an experiment in the same way as that for Kamakura's grasp types. Three subjects (Subject-A, Subject-B and Subject-C) performed Cutkosky's 16 grasp types. The subjects performed each grasp type with objects of different volumes. Two objects of different volumes are used at every grasp type. The total number of the grasped objects is thirty-two. Thus, three data sets were generated.

1) Placement Selection Results (Cutkosky): Our method was used to determine the placement of tactile elements to recognize the 16 grasp types based on the contact information of each data set. The selected placements for each subject are shown in Fig. 9. The placements consist of 40, 38 and 34 tactile elements for each subject. The density of the selected elements on the thumb and the index finger is higher than that on the other fingers and the palm.



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

Fig. 9. Effective placements of tactile elements for the recognition of Cutkosky's grasp types.

2) Evaluation of the Selected Placements of Tactile Elements (Cutkosky): We evaluate the recognition performance and the generality of the selected placement in the same way described in Section IV-A. The placements are shown in Fig. 9, and the recognition rates are shown in TABLEs V and VI. These results are similar to those for Kamakura's grasp types. The effect of the pruning was also investigated in the same way described in Section IV-A4). The result is shown in Fig. 10 and TABLE VII.

TABLE V
RECOGNITION RATES [%] (THE SEVEN COMPOSITIONS OF INPUTS, CUTKOSKY).

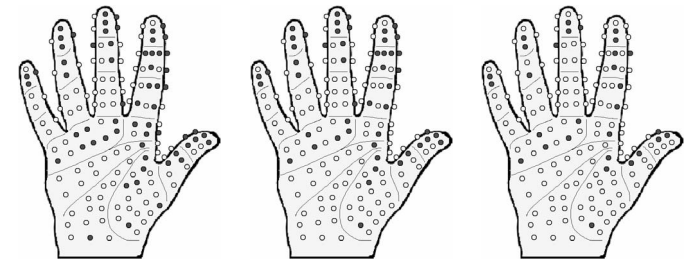
Input data				Recognition rates [%]		
No.	Sel-Co	NoSel-Co	Angle	SubjectA	SubjectB	SubjectC
I	√	√	√	100	99.9	90.7
II	√		√	100	99.9	90.0
III		√	√	83.6	99.9	80.6
IV			√	81.6	99.9	77.5
V	√	√		84.8	88.7	86.9
VI	√			84.8	88.7	86.8
VII		√		62.0	65.1	63.9

TABLE VI
RECOGNITION RATES [%]: THE EVALUATION DATA (COLUMN) OF ONE SUBJECT ARE RECOGNIZED BY USING THE PLACEMENT (ROW) OF ANOTHER SUBJECT, CUTKOSKY.

Placements \ Evaluation data	A	B	C	average
Placement-A	84.8	88.7	84.6	86.0
Placement-B	82.1	88.7	84.1	85.0
Placement-C	79.4	86.1	86.8	84.1

V. CONCLUSIONS

We developed a decision method for the effective placement of tactile elements for grasp type recognition. Unlike previous



(a) without pruning (62 elements) (b) pruning I (50 elements) (c) pruning II (30 elements)

Fig. 10. Reducution of the number of selected tactile elements by pruning for the recognition of Cutkosky's grasp types. (a) The selected placement without pruning. (b) pruning I: The selected placement with pruning (The specified number S is 10). (c) pruning II: The selected placement with pruning (The specified number S is 29).

TABLE VII
RECOGNITION RATES [%]: EVALUATION DATA (COLUMN) ARE RECOGNIZED BY USING THE PLACEMENTS SELECTED WITH PRUNING (ROW), CUTKOSKY.

The number of selected elements	Subjects			average
	A	B	C	
160	84.8	88.7	86.9	86.8
62	84.8	88.6	86.9	86.8
50	84.7	88.2	86.6	86.5
30	79.6	86.6	84.3	83.5

research that determined the placement of tactile elements empirically, this paper is a pioneering report for mathematically deciding the effective placement for the recognition of grasp types. The selection of effective placement is useful for designing devices that measure contact information for the recognition of grasp types in an arbitrary grasp taxonomy.

In two experiments, we used the types of grasp taxonomy defined by Cutkosky and Kamakura as benchmarks for the placement of tactile elements. Not only did a placement decided by our method require less than 40 tactile elements, it was also found that the recognition performance was as high as those using 160 tactile elements. When only the contact information was used for the recognition of grasp types, the recognition rates were more than 83%. The recognition performance was improved by using both the joint-angle information and the contact information. In this sensor fusion, the recognition rates were about 100%. In the view point of sensor fusion, the effective measurement of contact information is useful for previous work using joint angles for the recognition of grasp types.

The proposed method is extended by applying a decision tree pruning. The selected tactile elements were reduced by applying the simple pruning method in the experiments. In the case of Kamakura's grasp taxonomy, although the number of the selected elements was reduced from 66 to 26, its recognition rate of grasp types dropped only from 89.0% to 88.1%. By applying more effective pruning method, the selection of effective placement of tactile elements will be improved. A more standard placement for the recognition of grasp types will be obtained by applying the method to the contact information collected from a considerable number of subjects. However, as the number of contact information used in the method increases, so does the number of selected tactile elements. The pruning will be useful for reducing the number of selected tactile elements without badly dropping the recognition rate.

The recognition of grasp types has several applications. One of them is the grasp planning based on grasp preshape of a robotic hand. A proper grasp preshape will be selected from the recognized human grasp type in this grasp planning. Another application is the segmentation of continuous human hand motion for a task planning of a robotic hand. When performing a manipulation task, the human selects the proper grasp type depending on the shape of the grasped object and the purpose of the manipulation task. Grasp type can be used as keys to segment continuous human hand motion according to the meaning of the particular motion in the context of the tasks. The recognition of grasp types is useful to measure the transition of grasp types in the manipulation task. Motion primitives of the robotic hand will be created from the segmented hand motions, and a sequence of motion primitives to accomplish the task is also obtained from the sequence of the segmented hand motions labeled by the grasp type.

Future work is as follows. We will collect contact information of a considerable number of subjects, and decide a standard placement of tactile elements for the recognition of grasp types. We also will re-design a sensor glove by using analog tactile sensors instead of binary switches. The sensor glove used in this paper is equipped with binary switches whose threshold value is 1[N]. The experimental result shows that binary contacts are apparently sufficient to discriminate among most grasp types. However a human hand obtains much information at the initial contact while the contact force of each contact point is less than 1[N] [28][29]. The present sensor glove may not be enough to provide significant information about the grasp types at the initial contact between a hand and an object. Therefore in future work, while considering the several types of tactile sensors have reported [30][31][32], we will re-design a sensor glove by using analog tactile sensors instead of binary switches.

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