2008 IEEE International Conference on
Robotics and Automation
Pasadena, CA, USA, May 19-23, 2008

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

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***Abstract*— The present paper describes a decision method for the 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 a recognition performance that is as high as that of a placement consisting of many tactile elements. The effective placement of tactile elements decided by the proposed method has been evaluated through experiments involving the recognition of grasp type from grasp taxonomy defined by Kamakura [1].**

I. Introduction

A multi-jointed multi-fingered robotic hand [2] is a potentially as dexterous as a human hand [3]. However, it is very difficult for us to manually and directly write a motion program of multiple 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 and is then somehow transformed into a motion program of a robotic hand. There are two approaches to teaching-by-showing: direct mapping and symbolic programming.

Generally, there are several differences in structure between the human hand and a robotic hand, including the number of fingers, the number of joints, and the disposition of the fingers. Therefore, it is not straightforward to utilize the data obtained by human workers in teaching-by-showing methods. Direct mapping of the joint angle trajectories of the human hand onto the robotic hand will not generate the same manipulation task. Another method of teaching is to generate joint angle trajectories of the robotic hand from the fingertip trajectories of the human hand in a Cartesian coordinate system by solving the inverse kinematics of the robotic hand. However, this technique often fails to maintain the stable grasp of an object because the possible directions and magnitudes of the exerted force are not suitable as a result of the difference in the finger configuration, even if the fingertips of the robotic hand maintain the same positions as those of the human hand. Force control is therefore required in order to overcome error in human motion measurement. Moreover, some joints may exceed the limits of rotation angles. Wang et al. proposed a method of modifying the 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].

A task program for the robotic hand would be autonomously generated if the actual task being executed by a human were recognized from the motion data of a human hand obtained through the teaching-by-showing process. Related research on human motion recognition has been reported in [5][6][7][8][9][10][11], and 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 as a sequence of symbols, each representing a particular manipulation. Adequately abstracted symbols enable the development of corresponding motion primitives that can be generated by a robot hand. The robot system would then be able to autonomously 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, recognition often fails 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 to improve 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].

The placement of tactile elements is important when recognizing manipulation tasks using contact information. For example, too many elements would obstruct the human hand during a manipulation task. In addition, the installation of several elements on a tactile sensing glove is difficult.

The objective of the present study is the development of a mathematical decision method for the effective placement of tactile elements for manipulation task recognition. Although the effective placement consists of a small number of tactile elements, the method has a recognition performance that is as high as that of many tactile elements. In previous research, the placement of tactile elements has been decided empirically.

The remainder of the present 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 the measurement devices used

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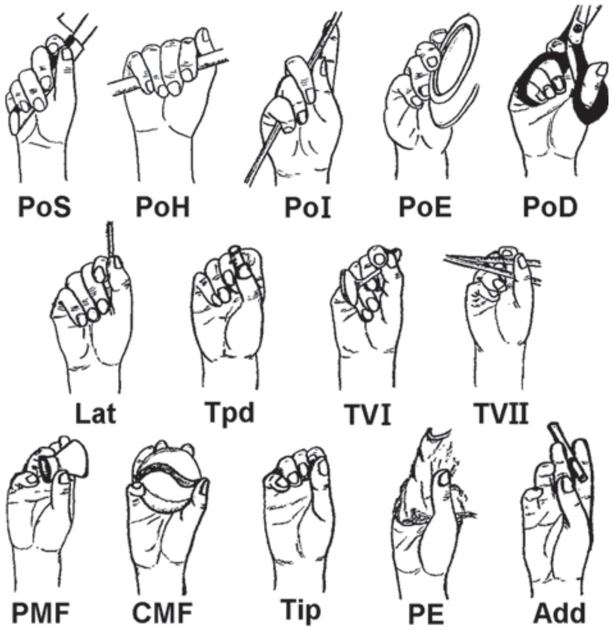


Fig. 1. Kamakura's taxonomy of prehension [1].

to obtain the contact information and the joint angle trajectories. Section IV describes the experiments for recognizing grasp type from grasp taxonomy, as defined by Kamakura (Fig.1). Section V presents the conclusions of the present study.

II. Decision Method for the Placement of Tactile Elements

We propose a decision method for the placement of tactile elements. First, a human subject performs manipulation tasks and obtains contact information with the tactile elements installed on a glove. The decision method then selects an effective placement of tactile elements using the contact information.

The proposed method selects an effective placement by using ID3 (Iterative Dichotomiser 3) [15], which is a kind of supervised learning algorithm. Based on Occam's razor, ID3 constructs a small decision tree. ID3 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 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 and 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 a 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 the 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).

The proposed method constructs a decision tree by using ID3, where the inputs are the tactile elements and the outputs are the labels of the recognized manipulation tasks. The set of training data consists of the contact information obtained through demonstration of the manipulation tasks. 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.

III. Measurement Devices

We use two types of sensors to measure human hand motion, namely, a tactile sensing glove designed by the authors and a data glove.

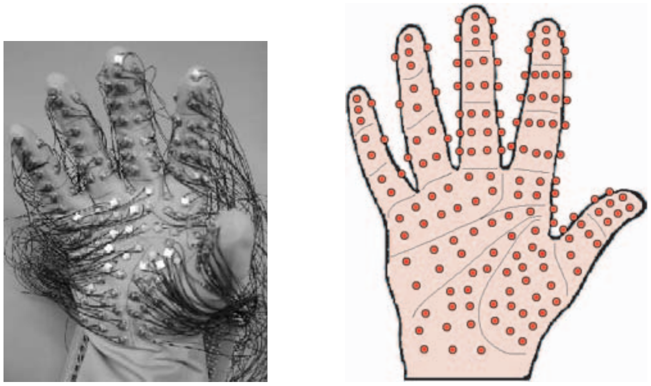
A. Contact Information

To measure the positions of contact points between a 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 and the placement of the 160 switches are shown in Fig.2. The 160 switches are represented by circles in Fig.2 (b). The circles outside the contour of the hand indicate switches that are distributed on the sides of the fingers.

Alternative switches, which output binary data of 'ON' or 'OFF', are used for the glove. The thickness of each switch is 0.8 mm, and the switches are squares having sides of 5 mm. The thickness of the contact mechanism of the switch is 0.4 mm, and the contact mechanism is circular, having a diameter of 3.2 mm. When a force of more than 1.0 [N] is exerted on the contact mechanism, the switch outputs the value of 'ON'. Contact information is 160-dimensional binary data provided from the 160 switches of the tactile sensing glove.

B. Joint-angle Information

We use a Cyber Glove (CG1802-R: Immersion Corporation) as an input device for measuring the joint angles of a human hand. The appearance and specifications of the glove are shown in Fig.3 and Table I, respectively. The Cyber



(a) (b)

Fig. 2. (a) Photograph of the tactile sensing glove with 160 switches. (b) Placement of the 160 switches.

Glove can measure the angles of the eighteen joints of a human hand. In order to recognize a manipulation task, we use the angles of sixteen joints, excluding two joints of the wrist. The positions of the sixteen joints are shown in Fig.4. The proximal joint of the thumb has two DOFs, and the other fifteen joints have one DOF. The joint-angle information is in the form of a 16-dimensional vector provided by the Cyber Glove.

Fig. 3. Photograph of 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. Manipulation Tasks

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

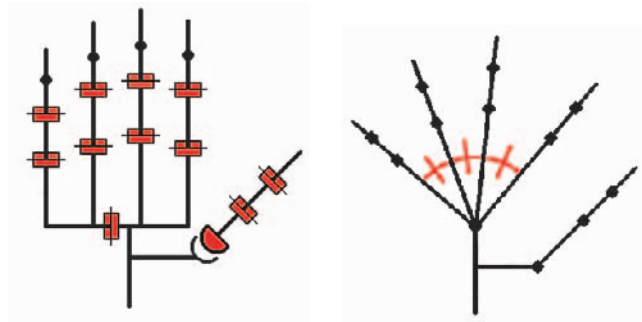


Fig. 4. Positions of the measured joints of the Cyber Glove.

We collected three data sets, each of which consists of the contact information and joint-angle information of the 14 grasp types demonstrated by the subject. The subject wore the tactile sensing glove over the Cyber Glove while performing the grasp types. The subject performed each grasp type with two objects of different shape. The subject grasped objects commonly encountered in daily life (Fig.5). The mass of the objects ranged from 0.9 [g] to 334.9 [g]. The subject reproduced each grasp type 100 times in random order. Three subjects (Subject-A, Subject-B and Subject-C) performed the grasping tasks, thus generating three data sets. The three subjects were males of age 23 to 32 years.

Fig. 5. Photographs of the grasped objects.

Although the thickness and the 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. All of the objects used in the grasping tasks were light in weight. Therefore, the influence of weight on the sensor readings is negligible.

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

B. Placement Selection Results

The 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 placement for each subject is shown in Fig.7. The placements consist of 27 to 33 tactile elements.

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

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

C. Evaluation of the Selected Placements of Tactile Elements

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 [16]. The algorithm was implemented using Weka [17], 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 validation on the seven data sets. The seven data sets are as follows.

① Contact information from all of the elements (All-Co.).
② Contact information from the selected elements (Key-Co.).
③ Contact information from all the non-selected elements
(NKey-Co.).
④ Joint-angle information and contact information from all of 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 non-selected elements
(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.

The results of the evaluation are summarized as follows.

- From input data ①④⑦:
  Although the recognition rates obtained by using the joint-angle information without the contact information ⑦ or the contact information from all of the elements ① are approximately 90%, the recognition rates obtained by using both the joint-angle information and the contact information ④ are approximately 100%. Thus, sensor fusion improves the recognition performance.

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

- From input data ①②③:
  The recognition rates obtained by using the contact information from the selected elements ② are as high as those obtained by using the contact information from all 160 elements ①. On the other hand, the recognition rates obtained by using the contact information from all non-selected elements ③ are reduced. Although the selected placements consist of small numbers of tactile elements, they have recognition performances that are as high as the rate for many tactile elements.
- From input data ④⑤⑥:
  Similar results are obtained when contact information is integrated with joint-angle information④⑤⑥.

D. Generality of the Selected Placements of Tactile Elements

In order to evaluate the generality of the selected placement, 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 of one subject ② are recognized using the placement of another subject.

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

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

E. Comparison of the Effective Placements of Tactile Elements and Locations of Human Mechanoreceptive Units

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

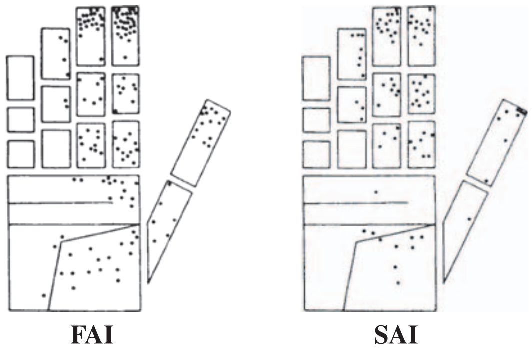


Fig. 8. Locations of the receptive field centers of two types of mechanoreceptive units (FAI and SAI units) [19].

V. CONCLUSIONS

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

ACKNOWLEDGMENTS

The authors thank Tsuyoshi Yokoya for his assistance with the data acquisition.

REFERENCES

[1] N. Kamakura *et al.*: "Patterns of static prehension in normal hands", The American Journal of Occupational Therapy, Vol. 34, No. 7, pp. 437-445, 1980.
[2] H. Kawasaki, H. Shimomura and Y. Shimizu: "Educational-industrial complex development of an anthropomorphic robot hand 'Gifu hand"', Advanced Robotics, Vol. 15, No. 3, pp. 357-363, 2001.
[3] A. Bicchi: "Hands for Dexterous Manipulation and Robust Grasping: A Difficult Road Toward Simplicity", IEEE Transactions on Robotics and Automation, Vol. 16, No. 6, pp. 652-662, 2000.
[4] H. Wang, K. H. Low, M. Y. Wang and F. Gong: "A Mapping Method for Telemanipulation of the Non-Anthropomorphic Robotic Hands with Initial Experimental Validation", Proceedings of the 2005 IEEE International Conference on Robotics and Automation, pp. 4229-4234, 2005.
[5] S. B. Kang and K. Ikeuchi: "Toward Automatic Robot Instruction from Perception - Mapping Human Grasps to Manipulator Grasps", IEEE Transactions on Robotics and Automation, Vol. 13, No. 1, pp. 81-95, 1997.
[6] T. Mori, Y. Segawa, M. Shimosaka and T. Sato: "Hierarchical Recognition of Daily Human Actions Based on Continuous Hidden Markov Models", Proceedings of the 6th IEEE International Conference on Automatic Face and Gesture Recognition, pp. 779-784, 2004.
[7] K. Ogawara, J. Takamatsu, H. Kimura and K. Ikeuchi: "Generation of a task model by integrating multiple observations of human demonstrations", Proceedings of the 2002 IEEE International Conference on Robotics and Automation, pp. 1545-1550, 2002.
[8] J. Aleotti and S. Caselli: "Grasp Recognition in Virtual Reality for Robot Pregrasp Planning by Demonstration", Proceedings of the 2006 IEEE International Conference on Robotics and Automation, pp. 2801-2806, 2006.
[9] S. Ekvall and D. Kragic: "Grasp Recognition for Programming by Demonstration", Proceedings of the 2005 IEEE International Conference on Robotics and Automation, pp. 760-765, 2005.
[10] Keni Bernardin, Koichi Ogawara, Katsushi Ikeuchi and Ruediger Dillmann: "A Sensor Fusion Approach for Recognizing Continuous Human Grasping Sequences Using Hidden Markov Models", IEEE Transactions on Robotics, Vol. 21, No. 1, pp. 47-57, 2005.
[11] M. Kondo, J. Ueda, Y. Matsumoto and T. Ogasawara: "Perception of Human Manipulation Based on Contact State Transition", Proceedings of the 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 100-105, 2004.
[12] J. R. Napier: "The prehensile movements of the human hand", The Journal of Bone and Joint Surgery, 38B, 4, pp. 902-913, 1956.
[13] M. R. Cutkosky: "On grasp choice, grasp models, and the Design of hands for manufacturing tasks", IEEE Transactions on Robotics and Automation, Vol. 5, No. 3, pp. 269-279, 1989.
[14] Y. Seki, S. Sato, M. Shimojo and A. Takahashi: "Development of a New Hand-Grasp Measurement System", Proceedings of HCI International, 20B, pp. 791-796, 1995.
[15] J. Ross Quinlan: "Discovering Rules by Induction from Large Collections of Examples", In Expert Systems in the Micro-Electronic Age, D. Michie, Editor, Edinburgh University Press, Edinburgh, UK, pp. 168-201, 1979.
[16] J. Friedman, T. Hastie and R. Tibshirani: Additive Logistic Regression: a Statistical View of Boosting, The Annals of Statistics, Vol. 28, No. 2, pp. 337-374, 2000.
[17] Ian H. Witten and Eibe Frank: "Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations", Morgan Kaufmann Publishers, 1999.
[18] A. B. Vallbo and R. S. Johansson: "Properties of cutaneous mechanoreceptors in the human hand related to touch sensation", Human Neurobiology, Vol. 3, pp. 3-14, 1984.
[19] R. S. Johansson and A. B. Vallbo: "Tactile sensibility in the human hand: Relative and absolute densities of four types of mechanoreceptive units in glabrous skin", Journal of Physiology, Vol. 286, pp. 283-300, 1979.