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# Statistical Manipulation Learning of Unknown Objects by a Multi-Fingered Robot Hand

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This paper proposes a learning method for multi-fingered manipulation of unknown objects. The method is a combination of higher-order local autocorrelation (HLAC), principal components analysis (PCA), and mean-shift clustering. Our results show that the different geometric restrictions of manipulation maximize the variance in the space of feature vectors identified by HLAC analysis. As a result, the data corresponding to each manipulatory act are clustered in a high-dimensional space in accordance with the restrictions via PCA. Mean shift clustering method classify the clusters which correspond the restrictions. The efficacy of the proposed method is shown by means of handling experiments of given diameter caps subjected to rotational restriction.

*Keywords*: Manipulation learning; Statistical analysis; Higher-order local autocorrelation.

## 1. Introduction

In order to learn to perform tasks in the real world, robots need to be equipped with some means to acquire on-site a working model of the task, and to generate on-line a control strategy. Opening a bottle, for instance, involves (a) understanding the motion constraints of the bottle, that is, the bottle can be opened only by rotating the cap in one direction (working model); and (b) generating appropriate finger movements (control strategy). Both problems are not trivial.

On possible way to tackle them is through an on-line learning strategy known as learning by watching [1], [2]. The core idea is that the learning robot first observes the actions performed by another robot or a human, then generates an internal working model of the action sequence, and finally reproduces the observed actions. The strategy is sequential. The main drawbacks of learning by watching are (a) the assumption of enough information to build the internal model, and (b) the fact that others' behavior is observed passively. Indeed, by only passively observing others behavior it is difficult to acquire enough information for behaving in the real world, unless the environment is not well-conditioned.

There are a host of other studies on manipulation that have focused either on the construction of a physical model of the manipulated object, or on the learning of appropriate manipulation strategies. Previous studies have also acknowledged the necessity of modifying the working model by trial and error. Such exploratory movements have been limited, however, to behavioral optimization, and have neglected the on-site acquisition of a working model. Probe manipulation for instance, has typically taken into account the position and the orientation of the manipulated object [3], [4], but ignores its motion constraints.

Here, we introduce an "asymptotic approach" to the acquisition of the working model, and to the learning of the control strategy, which is based on trial-and-error exploratory movements. Trial-and-error is seen as a basic requirement of our approach because typically in a manipulation task, the robot does not possess any a priori information about its hand or about the manipulated object and its motion constraint. By means of repeated trials and errors it can construct both working model and manipulation strategy.

More specifically, this paper deals with an on-site basic learning system for manipulation with a robot hand that was developed for manipulation learning. The robot hand features joint-angle sensors at every joint and has a high compliance. As a task we choose coarse exploration of implicit motion constraints of unknown caps of bottles which had to be opened. We used higher-order local auto-correlation (HLAC) [5] (typically employed as an image recognition method) to transform the time series sensor values sampled by the hand into a high-dimensional feature vector. Then, we applied principal component analysis (PCA) to compress the space of feature vectors, and to identify clusters. We found that different attributes of each manipulation maximized the variance in feature space. Mean shift clustering [6] classifies the PCA data regarding to the environment property.

Section 2 defines a manipulation learning and describes its requirements. In section 3 we develop a high compliant robot hand for the manipulation learning. Higher-order local auto-correlation modified for the learning, principal component analysis and mean shift clustering are introduced in section 4. This three statistical methods are able to extract and classify patterns in the manipulatory activity. We show experimental results by the methods in section 5. Section 6 concludes the efficacy of the robot hand and the methods.

## 2. System for manipulation learning

### 2.1. *A child learns to manipulate an unknown object*

Consider for a moment a care-giver opening a bottle (Fig. 1) close to a child. Driven by curiosity, and other types of intrinsic motivational forces, the child keenly observes what the care-giver does. Because children are curious and eager to do what their parents do. The child starts to imitate the parent doing.

The child then makes trial manipulations based on its observations. The child's observations are not complete, because of the obstacles posed by arms, hands and fingers of the parent and the invisible factors of manipulation such as force, friction and so on. The hypothetical manipulations generated from incomplete visual input are often ineffective. We define the hypothetical manipulation as a coarse manipulation. The child touched and manipulated the bottle in different ways.

Sometimes the child tries to open the bottle by gripping at a bottle body instead of the cap. It is not possible. Sometimes the child incidentally opens the bottle. The child discovers a physical law by its own behavior. A definition of manipulation learning by imitation is above. Therefore, a learning actor which has to learn the bottle cap task requires a classification ability of the motion constraints.

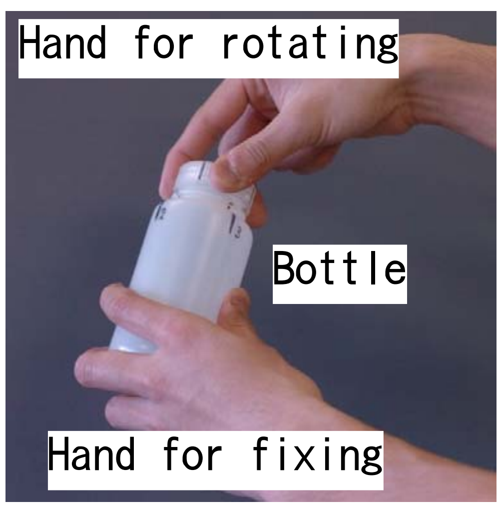


Fig. 1. Open bottle cap task by people hand

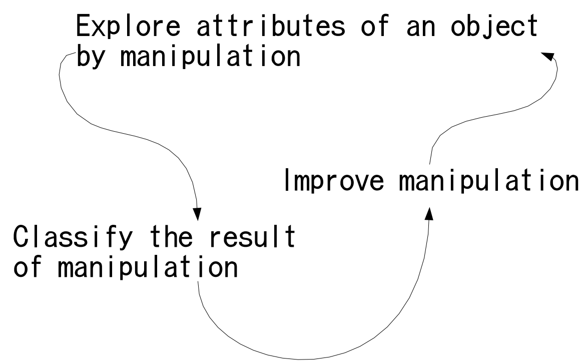


Fig. 2. Manipulation learning loop

### 2.2. *Hand priority grasp for manipulation learning*

A robot that learns to manipulate should autonomously gather information in the process and use such information to improve its task performance. If the robots movements are not completely random, it is plausible to assume that the information collected by the robot has some intrinsic structure. We therefore need a novel grasping strategy which depends on the information structure.

As shown in Fig. 3, the hand Priority Grasp (HPG) [7] is composed of four phases.

(1) Approach phase: Fingers approach the object to be manipulated.
(2) Initial touch phase: One finger contacts the object while all fingers are coming closer together.
(3) Initial grab phase: Each finger touches the object as the hand closes, and the enclosing fingers rotate the object.
(4) Stable grasp phase: The fingers and the object reach a stable position if there is enough friction condition between them.

The Object Priority Grasp (OPG) depends on the traditional balance mechanism between a hand and the manipulated object. It requires the position and the orientation of the object for balancing and needs precise information about the object before the object is grasped. However, how can such this information be obtained without touching?

The HPG does not need a priori information because the hand interacts with the manipulated object: the hand affects the object and the object affects the hand. Through this reciprocal interaction, the hand acquires information about manipulated object. The HPG is therefore suitable for manipulation learning in which the learning system has no a priori information about the manipulated object.

The HPG mechanism for removing a bottle cap is shown in Fig. 4. The finger applies a force vector to the bottle cap, but this vector is not directed toward the center of the cap. Because the center of the cap acts as a virtual finger, it is possible

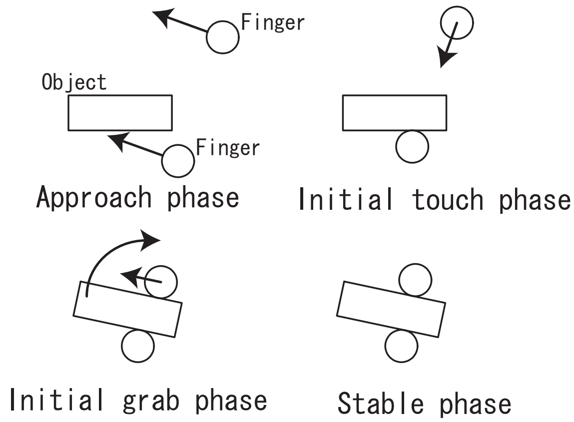


Fig. 3. The four phases of the Hand Priority Grasp.

to rotate the cap is effectively rotated by two fingers. This mechanism cannot reach the stable phase, however, because the friction between the finger and the cap decreases as the rotates. Finally, the finger slips from the cap and falls away.

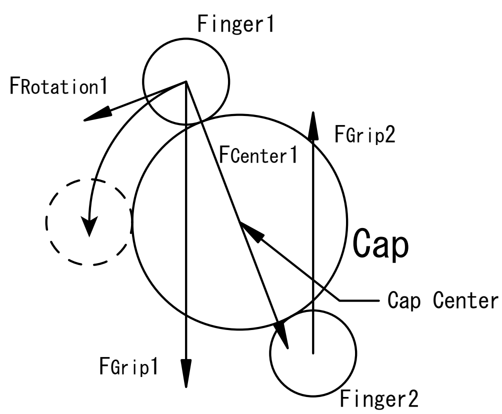


Fig. 4. HPG Robot fingers rotates a bottle cap by working against virtual finger at the center of the bottle cap.

### 2.3. *Manipulation learning by a robot hand*

Manipulation learning by a robot hand consists of the three steps shown in Fig. 2.

(1) Probe manipulation: A manipulated object has many attributes (constraint, weight, size, and so on), and the robot hand explores them in the process of manipulation.

(2) Clustering of manipulation result: If a robot hand manipulates randomly, the manipulation results can be grouped into classes according to the ways they are restricted by the attributes of the manipulated object.
(3) Improvement of manipulation: One condition as physical restriction corresponds one class which is generated by the learning method. The learning method generates knowledge about the situation the robot is dealing with. We can expect that the class can be used for improving the manipulation for the task.

We implemented this three-step learning process in our basic learning mechanism. It is important to note that this process is not a loop.

## 3. Development of robot hand for learning

### 3.1. *Humanoid Multi-Fingered Robot Hand*

The human hand has four fingers, one thumb, many actuators (muscles) and many sensors (organs of somatic sensation). We focus here on actuation and joint-angle sensation because they are important for manipulation learning. A robot hand can observe its manipulations by monitoring changes in joint angles, which characterize the interaction between the hand and the manipulated object.

Two features of the robot hand we developed are its high compliance and angle sensor at all joints. The high compliance facilitates the transfer of external environment property (about target moving, constraint, and so on) to the internal state of the hand. The low mass of the fingers and the thumb is kept compliance by putting all the actuator that are usually heaviest parts in the palm frame. High compliance enables the robot hand and the environment to interact with dynamics. The fingers and thumb also have soft rubber fingertips for compliance. Converging the motors in the palm frame is implemented by tendon driven mechanism.

A top view of the robot hand is shown in Fig. 5. The joints give the hand 18 passive degrees of freedom, and the motors give it 10 active degrees of freedom. The three-joint fingers are curled by a coupled tendon-driven mechanism[8]. The mechanism enables the number of active degrees of freedom to be reduced, so the number of motors is less than the number of joints. The reduction gives joint angles of finger uncertainty. The uncertainty is observed by joint-angle potentiometers at each joint.

The configuration of degrees of freedom is shown in Fig. 6. The discontinuous-line circles indicate joints or series of joints that are driven by one motor and thus represent a single active degree of freedom. Each finger has two motors, one that moves three joints simultaneously and one responsible for lateral movement. The thumb also has two motors, one for the base joint and one for the fingertip joint. The thumb, forefinger and middle finger thus have a total of six active degrees of freedom that can specify the position and orientation of a manipulated object.

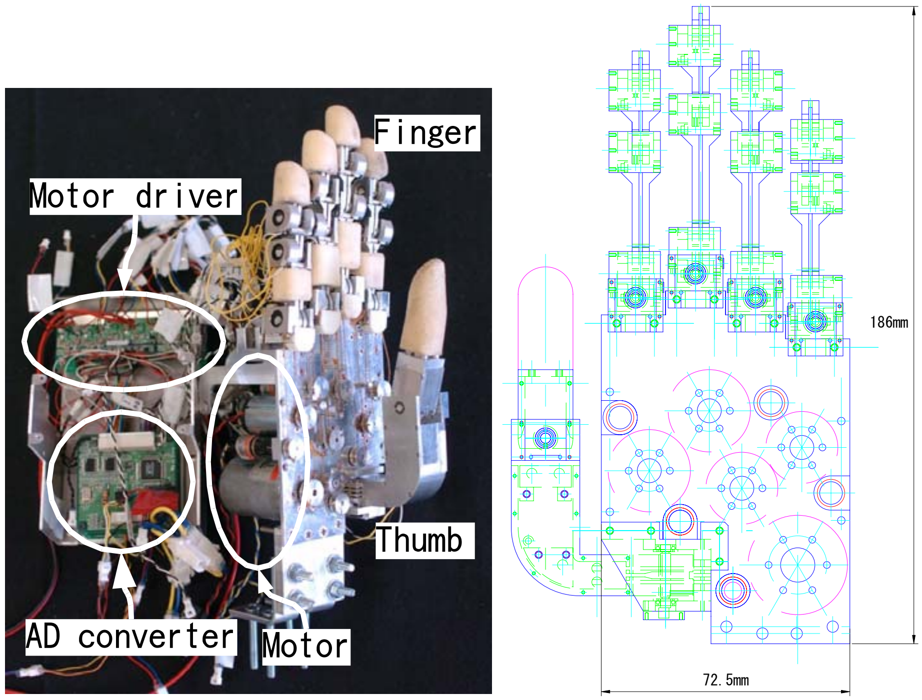


Fig. 5. Robot hand used in our experiments.

### 3.2. *Control System*

The control system is shown in Figure 7, and is based on RT Linux ( a real time operating system ). User space programs communicate kernel space program via an RT FIFO. Kernel space programs which are real time controller receive commands from user space and send control information ( sensor value, output voltage, and so on ) from the robot hand to user space. Kernel space programs drive PCI board driver. The PCI board[9], in turn, sends control packets to slave nodes. Slave nodes receive control packets and return packets such as the AD converter value by the nodes to the PCI board. The control frequency is 1 kHz.

## 4. Method

### 4.1. *Statistical feature for manipulation*

We assume the experimental results are represented in the form of a matrix in which joint channels are the columns and time series are the rows. The analysis procedure is shown in Fig. 8

(1) Step 1. HLAC is applied to the manipulation result matrices.
(2) Step 2. PCA is computed on the feature vector space resulting from Step 1.

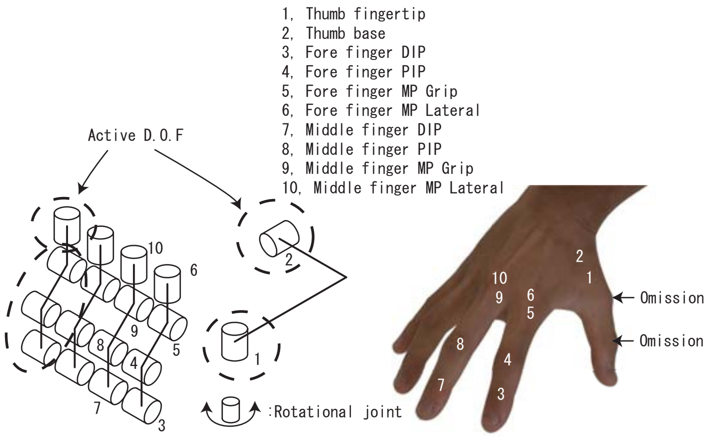


Fig. 6. Configuration of degree of freedom.

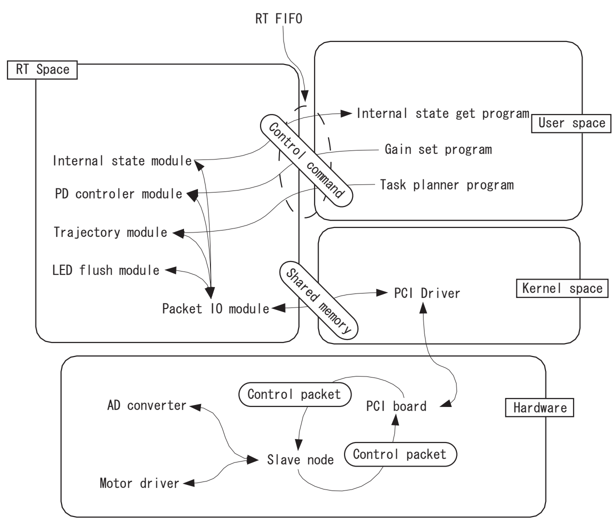


Fig. 7. Control system.

(3) Step 3. The principal component (Step 2) are mean shift clustered.

Step 1. HLAC feature (Eq. 1) is applied to the manipulation result matrices.

$$a(a_1, a_2, \cdots, a_n) = \int f(r) f(r + a_1) \cdots f(r + a_n) dr \qquad (1)$$

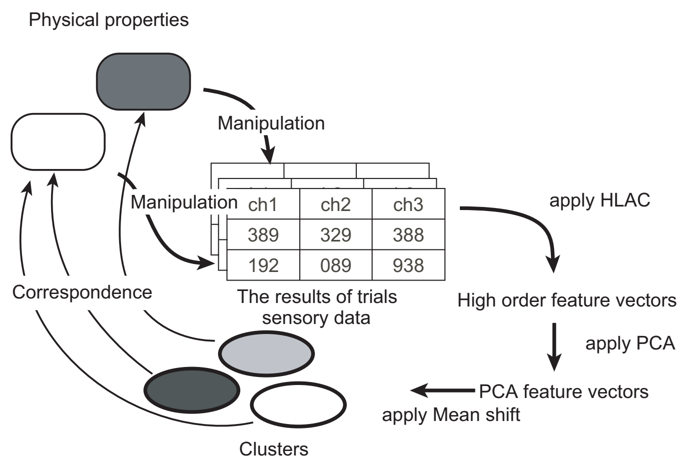


Fig. 8. The procedure of extracting manipulation property

a with left side is feature vector, r is pixel location of image and a with right side is direction vector of focusing feature. The direction vector can transform feature mask like Figs. 9 and 10. We use a form of HLAC for this analysis because it is particularly appropriate for detecting information from features of manipulation, since it was originally designed for use in image recognition. A basic feature of manipulation is that the correlations between the joint angles change with time.

Eq. 2 is relation between current and next time step of joint angles change with time:

$$x_{i=1\cdots m,t+1} = g(x_{i=1\cdots m,t}) \tag{2}$$

where $x_{i=1\cdots m,t}$ is sensing values, i is the number of sensors, t is time step, and $g()$ is some kind of relation about the hand, the manipulation, and the physical property.

For example, when people want to remove certain kinds of caps, the forefinger and middle finger move simultaneously in one direction while the thumb moves in the opposite direction. These finger movements are correlated and a manipulation can be represented by a pair of their correlations. Feature masks of HLAC are shown in Figs. 9 and 10.

In an image, the x direction has the same attribute of the y direction. HLAC feature masks are usually second order square masks (Fig. 9). In manipulation recognition, however, the channel direction does not have same attributes of as the time direction. Manipulation recognition is anisotropic, so the feature masks for it are first-order rectangular masks (Fig. 10). The horizontal direction of the masks is joint channel which has 10 joints as thumb, forefinger and middle finger. The vertical direction of the masks is time change. The reasonable number of time

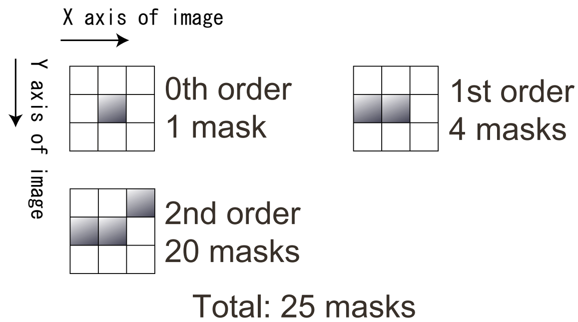


Fig. 9. Feature masks of High-Order-Local-Autocorrelation for image recognition.

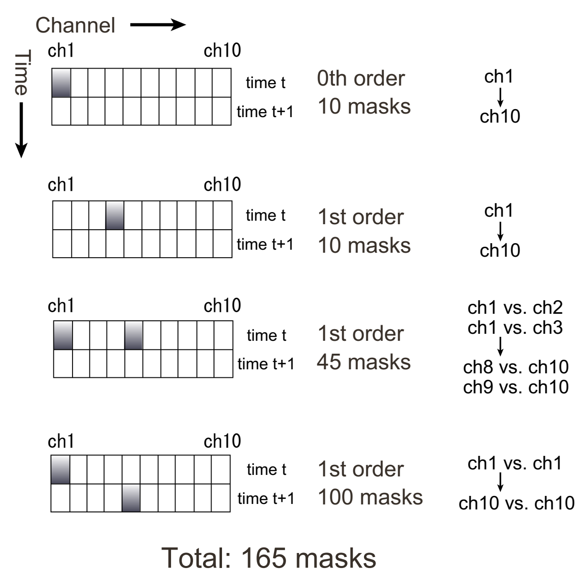


Fig. 10. Feature masks of High-Order-Local-Autocorrelation for manipulation recognition.

step still needs to be determined, but, we decided to use two time steps in our experiments. Corresponding between finger joints and joint angle sensor channels is shown in Table 1. Fig. 6 and Table 1 represent the anatomical configuration of joints and sensors.

Step 2. PCA is applied to the feature vectors of the previous correlation. We are able to get target disparity of manipulation result as HLAC feature. Because the performed experiment included an important ”control condition” (that is, the bottle cap), the distribution of the disparity of feature vectors could be maximized, and PCA could detect a space in which the variance could be maximized. PCA

Table 1. Finger joints and sensor channels mapping.

| | |
|---|---|
| Ch1 | Thumb fingertip |
| Ch2 | Thumb base |
| Ch3 | Fore finger DIP |
| Ch4 | Fore finger PIP |
| Ch5 | Fore finger MP grip |
| Ch6 | Fore finger MP lateral |
| Ch7 | Middle finger DIP |
| Ch8 | Middle finger PIP |
| Ch9 | Middle finger MP grip |
| Ch10 | Middle finger MP lateral |

can detect maximized axis of high order space. We expect that the distribution of control conditions is superior than other modifications and noise.

Step 3. Mean shift clustering is applied to the PCA vectors. Mean shift estimates probability density by sampling point. Mean shift depends only on data, and does not require a teaching signal or the number of clusters. Points corresponding to different properties are located in different areas of the PCA space. We expect mean shift to generate also some classes which corresponds to properties of the environment.

## 5. Experiments

### 5.1. *Experimental setup*

The experimental setup we used for manipulation learning is shown in Fig. 11. The Robot hand mounted on a stand tried to remove the cap from a bottle fixed to a mast.

We performed experiments under various conditions and analyzed the results statistically. The controller sent the same commands to the robot hand, and the hand executed manipulations under the influence of the experimental environment. The environment, in turn, affected by the hand and its state was translated to the internal state of the hand. In this sense, the robot hand interacted reciprocally and dynamically. It was hence possible to extract information about the environment from the manipulatory activity. Some manipulation primitives are described below.

(1) move the thumb, forefinger, and middle fingers closer to each other across the bottle cap.
(2) move the thumb and fingers in opposite directions.

The primitives are descrived as joint angle path and perfromed by PD control. The rotational manipulation is classified into circular disk grasp[10].

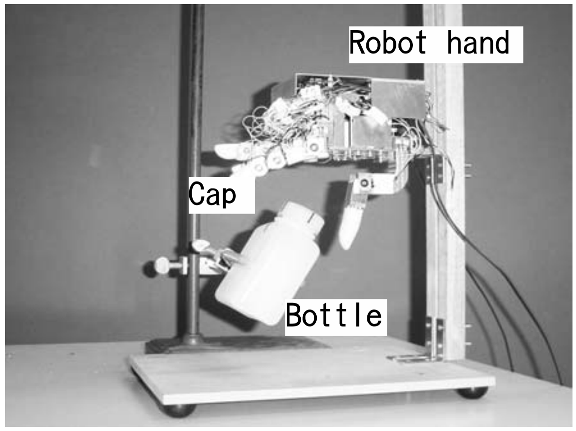


Fig. 11. Experimental setup.

The setup conditions are listed in Table 2. We designed the two motion constraints in a symmetric fashion, that is, the condition was the "free cap" rotation, whereas the second one was "fixed cap" rotation. Two motion constraints for each of three cap diameters yielded a total of six conditions. These were enough to confirm the feasibility of the robot hand and the statistical analysis used to extract the environmental conditions from the manipulation results.

Table 2. Condition matrix of experiment.

| Cap Diameter \Condition | Rotation: fixed | Rotation: free |
|---|---|---|
| 40mm | 24 trials | 24 trials |
| 45mm | 24 trials | 24 trials |
| 65mm | 24 trials | 24 trials |

Joint angles are expressed as wire travel distance at joint group with coupled tendon-driven mechanism, and as joint angle at other joints. Fingers for manipulation at this experiment, thumb, fore finger and middle finger, have 10 joints. The control system sampled joint angles at a rate of 50Hz. and experiment lasted 9 seconds. As a result, we obtained a 449x10 manipulation data matrix. HLAC which has 165 feature masks transforms this matrix to a 165-dimensional feature vector. We then applied PCA, and mean shift clustered the feature vectors. PCA contribution rate measures ratio of source data in superior dimensions of PCA analyzed data.

When the robot manipulates the free rotation cap, the fingers rotate smoothly with the cap together, When the robot manipulates the fixed rotation cap, the fingers rotate intermittently. Because friction between the robot and the cap forces the robot to move by on and off motion. We obtain a clear joint angle data from the free manipulation, and a noisy joint angle data from the fixed manipulation. The clear data generates a cluster which corresponds one condition. However the noisy data is parted to some clusters by noise component despite including only one condition.

### 5.2. *Recognition of the restrictions in each diameter*

One manipulation trial corresponds to one feature vector. We apply PCA to the feature vectors for each diameter. The left graph of Figs 12, 13 and 14 represents the 1st and 2nd PCA component for each diameter. The rights of the figures represent results of mean shift clustering. Mean shift clustering make some large clusters and many small clusters. The small clusters include a few trials. The rights of the figures represent only the large clusters and omit the small clusters. The contribution rates of this PCA are listed in Table 3. It is evident that the 1st and the 2nd components can approximately reconstruct the original information. We can see clusters corresponding to the control conditions. Comparison of the left and the right of the figures represents the correspondence.

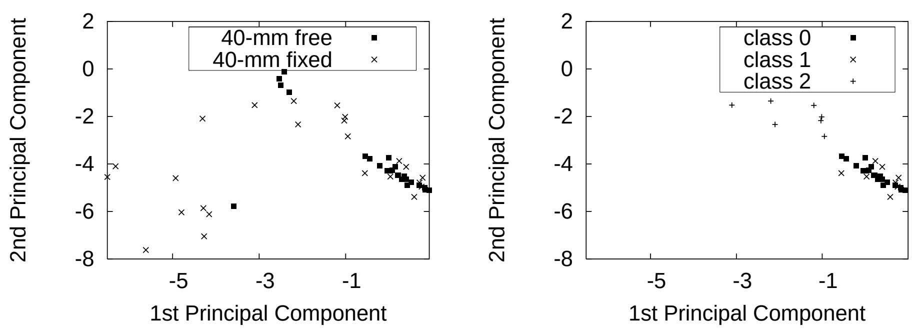


Fig. 12. Hand data from manipulating three lids with different diameters. Results of PCA are shown for each case.

Table 3. PCA contribution rate of the analysis shown in Figs. 12, 13 and 14.

| | 40mm | 45mm | 65mm |
|---|---|---|---|
| 1st | 0.427 | 0.620 | 0.529 |
| 1st + 2nd | 0.685 | 0.806 | 0.847 |
| 1st + 2nd + 3rd | 0.876 | 0.877 | 0.914 |

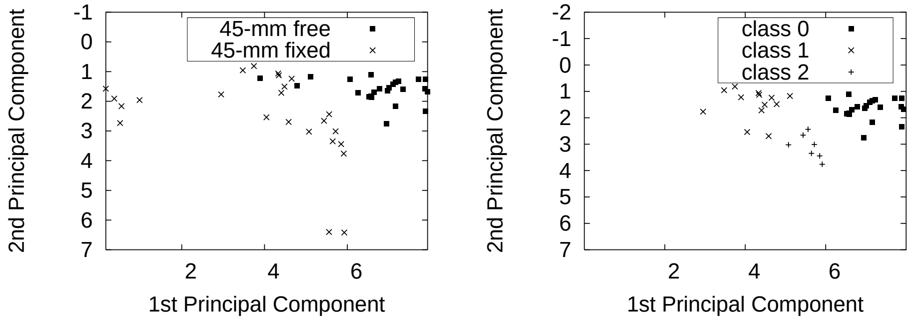


Fig. 13. Hand data from manipulating three lids with defferent diameters. Results of PCA are shown for each case.

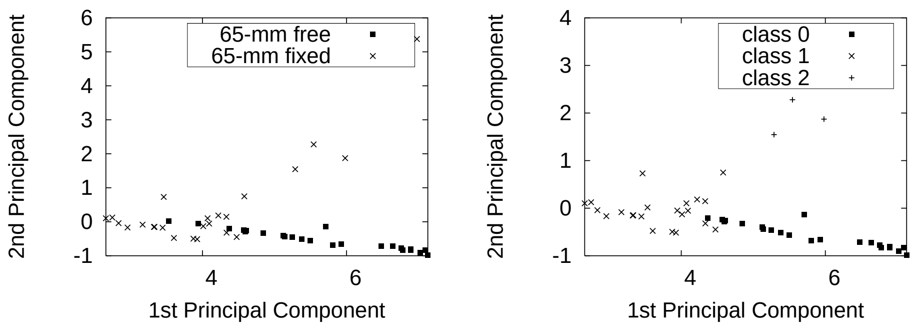


Fig. 14. Hand data from manipulating three lids with defferent diameters. Results of PCA are shown for each case.

### 5.3. *Recognition of the restriction in given diameters*

We analyze the result data which include all diameters. Shown in Fig. 15 is PCA and mean shift clustering. The right graph omits some classes which has few trials because of same reason above. Shown in Table 4 is PCA contribution rate. Cluster 1 to 3 in the left of Fig. 15 correspond classes in the right of Fig. 15.

Table 4. PCA contribution rate of the analysis shown in Fig. 15.

| | |
|---|---|
| 1st | 0.413 |
| 1st + 2nd | 0.724 |
| 1st + 2nd + 3rd | 0.824 |

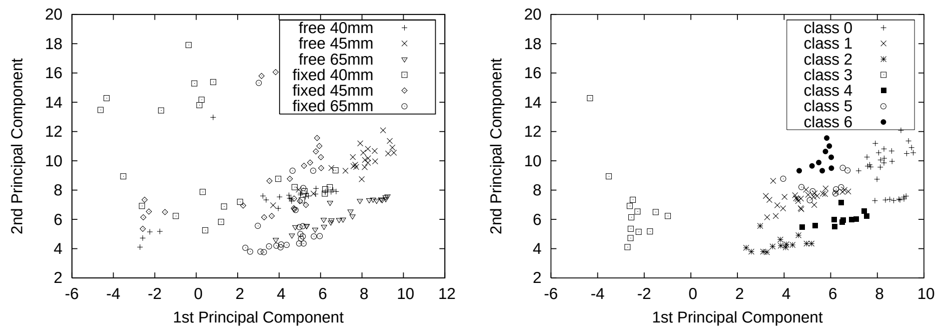


Fig. 15. Hand data for three different diameters. PCA result for the mixed data.

## 6. Conclusion

In this paper, we proposed a novel trial-and-error learning method for manipulation systems, which consisted of a combination of modified HLAC, PCA, and mean-shift clustering. The learning method was tested experimentally in a real world scenario in which a high compliant robot hand had to learn to open a bottle with caps of unknown diameter. Our results show that modified HLAC can successfully identify spatial and temporal correlations between pair of joints. By subsequently clustering the feature vectors of the correlation analysis we were also able to classify the manipulatory activity according to its interaction with the task environment.

One obvious limitation of the current framework is the reduced number of active degrees of freedom of the hand. This affects the hand's dexterity and manipulatory capabilities. Future work will hence be oriented at increasing the number of active degrees of freedom to make the hand more like the human hand, and its manipulation potential closer to the one of humans. Future research will be also aimed at improving the trial-and-error learning method. Currently, the manipulatory abilities of the robot hand do not change over time. Real world interaction with an unstructured and largely unknown environment, however, requires adaptivity. The same way people can improve their manipulation skills, we will try to develop a system capable of improving its manipulatory skill by using the statistical methodology outlined in this paper.

A last point will be to integrate various types of sensors (such as elements sensitive to pressure, temperature, slip, and so on). This will enable the hand to collect additional information about the manipulation environment. The rationale is that a learning system that has access to multiple sensors is able to construct a better working model. The kind of multi-modality learning system will provide us with the information required to improve robot manipulation, and to make it more like the kind of manipulation performed by people in their daily life.

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