Development of Smart Gripper For Identification of Grasped Objects

Nisit Kiwatthana† and Somyot Kaitwanidvilai*
†College of Data Storage Innovation, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand.
E-mail: residentwanderer@gmail.com
*Faculty of Engineering, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand.
E-mail: drsomyotk@gmail.com

Abstract— **Force control is one of the most important schemes in many industrial applications, especially in painting and grasping tasks. In practice, the proper control parameters in force controller is not easy because the performance of entire system does not only depend on the actuator dynamic, but also the environment and grasped object. In addition, several applications need to use the force control system for grasping various types of the object, this results in the dynamic change and poor performance in nature. To deal with this problem, the fast dynamic identification using a pair of input and output data is proposed to identify the plant dynamic of the force control system. The position and force are collected and used for the structured dynamic identification. Predefined clusters determined from several data sets of different objects are evaluated using K-means clustering. As seen in the experimental results, the proposed gripper system can identify the object group correctly.**

I. Introduction

In industrial applications, there are many methods to classify the pre-defined types of the objects such as image processing, roughness of surface, the shape of the object, etc. In several applications, the classification by observing only the physical properties cannot be achieved. Mechanical properties such as damping coefficient, mass, spring are also an alternative choice for using in classification process; however, these parameters need force and position sensors for the classification. In fact, in the industrial automation system, force and position sensors are normally installed in the system for control purpose. To enhance the ability of classification and gripper, this research focuses on the development of smart gripper which can identify the type of the grasped object using sensory data, i.e. force and position. Many researches regarding the object classification and robotic systems were proposed to enhance the ability of autonomous system [1-10]. The classification of the objects by analyzing of the direction of touch, temperature, roughness of the surface, etc. were proposed [1-10]. In [1], the identification of the target by applying exploratory procedures (EPs) to analyze force and direction, including the temperature were proposed. The results of the object classification results are better consistent with the proposed technique [1]. Classification of objects by sliding the robotic fingers along the surface were presented in [2]. In this paper [2], the analysis of frictional properties using the K-NN (K mean-Neural Network) classification were proposed. The 88.5% accuracy of the features of the 12 different surface models can be achieved [2]. Moreover, this technique was applied to the feet of the robot for classifying the type of floor areas in humanoid robot applications [3]. In [4], tactile sensors were designed to provide higher information, i.e. 3D force model. In this paper, dynamic 3D force mapping was presented. This technique can be used in the object classification.

One of the most important parameters in mechanical properties of the grasped object is the system dynamic parameter. Mass, spring and damper coefficients are well known as a good dynamic descriptor for the object. Mass-Spring-Damper system is typically used in many characterization studies such as the vibration of the system [5-6], the modeling of the object dynamic, the collision study of the car simulation model [7], etc. In addition, the mass-spring-damper system is typically used to model the dynamic in control-system application, power system modeling (mechanical parts of the generator, etc.) [8-9]. In [11], the demonstration of classification by using mechanical properties of the objects and the k-nearest neighbor algorithm (k-NN) was proposed [11]. The data was sensed from a tactile sensor array (skin) covering the robot's forearm. The development of the robot to be close to the human finger were shown in [12-13]. In [14], the analysis and experiments to define the object stiffness using an optical three-axis tactile sensor were presented. As seen in this paper, the improvement of dexterous grasping tasks in robotic fingers can be achieved [14]. In [15], the classification of the objects using a novel tactile-array sensor attached on the robot grippers was proposed. The developed sensor is based on the flexible piezo-resistive rubber. In [16], both designed model and simultaneous control of the motion and deformation of soft object was developed. The proposed technique uses the symmetric linear mass-damper-spring model to analyze the dynamical behavior [16].

This research focuses on the development of the smart gripper using the classification of the objects by assuming the system as the Mass-Spring-Damper system. The signal data from the force and position sensors are used in the identification process to identify the parameter in pre-defined transfer function. ARX or AR model is adopted for the parameter estimation and the classification of data is done by K-means clustering methods. In our experiment, the various cans are used as the grasped objects which the developed smart gripper can identify the type of can correctly. Only 3 samples of data are enough for the identification and classification, and the controller can identify the object group correctly. This means that the proposed system is able to apply in real-time application in the future work.

II. THEORIES

A. Mass-Spring-Damper system

Mass-Spring-Damper system is a fundamental principle that has been widely used to explain both simple and complex systems to understand the mechanical model easily. In this system, the dynamic model can be described by three parameters, i.e., mass *M* (kg), spring constant *k* (N/m) and the damping coefficient *b* (N s/m). The spring constant serves to restore the position of the mass to return to the balanced position as the original. The damper force, which has the direction opposite to the vibrating force, is proportional to the speed of the system. The structure of mass-spring-damper system is shown in the following diagrams.

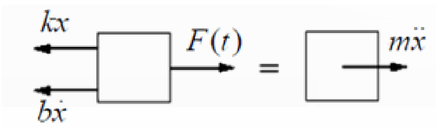


Fig.1 The diagram of the mass-spring-damper system.

By the analysis of force equations, the dynamic model of a mass-spring-damper system can be described as the following transfer function:

$$F = ms^2X(s) + bsX(s) + kX(s) \quad (1)$$

$$\frac{X(s)}{F(s)} = \frac{1}{ms^2 + bs + k} \quad (2)$$

Where F is the force and $x[m]$ is the displacement from the mass center to the reference point. *m, b* and *k* are mass, spring and damper coefficients, respectively.

B. System identification

In practice, system models can be identified or generated using three ways, those are, 1. Synthesis of mathematics, 2. Analysis of the model, 3. Using actual data. In many cases, estimation of the model parameters from using pure mathematical equations and several experimental setups is not feasible because this process is normally difficult and time consuming. In addition, many uncertain factors are not included in the mathematical model. To overcome this problem, the identification process by using several input-output pair data was proposed [17]. There are two types of this scheme, i.e. gray box and black box methods. In the gray box approach, pre-defined structure of the system is known while the system parameters are unknown. In contrary, in the black-box approach, both system structure and parameters are unknown. In this study, we applied the real sensory data from the robot encoders and the force sensors to be used in the model. To estimate the system parameters, the pre-defined dynamic in (2) is adopted and the standard model, ARX, is used as the estimating equation. The equation of ARX is shown in (3). Fig. 2 shows the typical model of ARX.

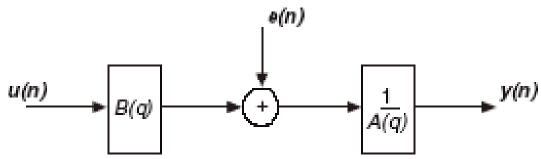


Fig. 2 ARX Model Structure

$$A(q)y(t) = B(q)u(t) + e(t) \quad (3)$$

Where *y(t)* is the output (position), *u(t)* is the input (force), *B* and *A* are the coefficient of the dynamic parameters, and *e(t)* is the error.

In discrete form, the equation in (3) can be converted to:

$$Y(z) = \frac{B(z)U(z)}{A(z)} + \frac{E(z)}{A(z)} \quad (4)$$

Based on (3), to determining the transfer function of the system using ARX model and gray-box modeling, the following parameters need to be assigned.

n_a = Order of the polynomial *A(q)*.

n_b = Order of the polynomial *B(q) + 1*.

n_k = Input-output delay expressed as fixed leading zeros of the *B* polynomial.

In this research, the parameters in (4) are the coefficient of terms *B* and *A*. The system is single-input single-output (SISO) system which the output is the position while the input is force.

C. K-Means Clustering

Clustering using K-means clustering technique is a well known technique for classification approach. This technique can automatically classify the group of data into subgroups when the number of data is very large. The algorithm in K-means clustering technique is simple and flexible by adjusting the mean of group data to minimize the distance from the center of the group. This process is done iteratively and the mean value of the new group will be calculated in the next iteration. This process is repeated until the middle of the group, no change or achieving a defined number of cycles. Parameters used in K-means-clustering technique to be quantitative variable must be interval-scale or rational-scale.

Followings show the steps for K-means clustering method. Given the number of groups *k*, the k-means algorithm is implemented in four steps:

1. Partition the objects into k nonempty subsets
2. Compute the seed points as the centroids of the clusters of the current partitioning (the centroid is the center, i.e., the mean value of the cluster)
3. Assign each object to the cluster with the nearest seed point
4. Go back to Step 2, stop when the assignment does not change

An example of K-Means Clustering is described in Fig. 3.

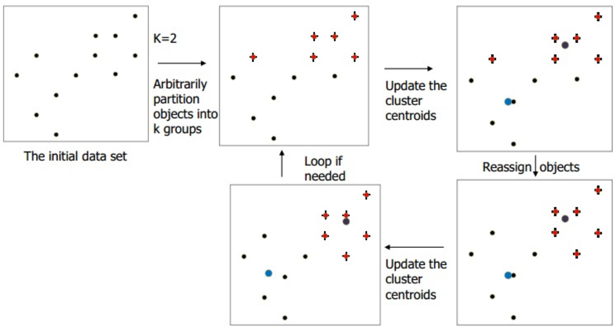


Fig.3 Technical process of K-means.

III. EXPERIMENTAL RESULTS

In our study, several commercial cans with liquid were used as the test object. Fig. 4 shows the samples used in our study. The smart gripper and robot adopted in our experiment are shown in Fig. 5. Epson robot with 20 µm accuracy and force sensors were used in our experimental setup. High accuracy encoder and force were installed on the developed gripper. Fig. 5 shows the experimental setup, robot arm and developed gripper in our study.

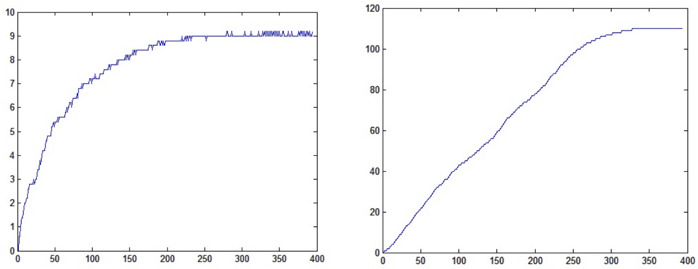
(a) (b) (c) (d)

Fig. 4. Photo of the test objects.

Fig. 5 Experimental setup

In our study, the process of identification of the smart gripper can be divided into two phases:

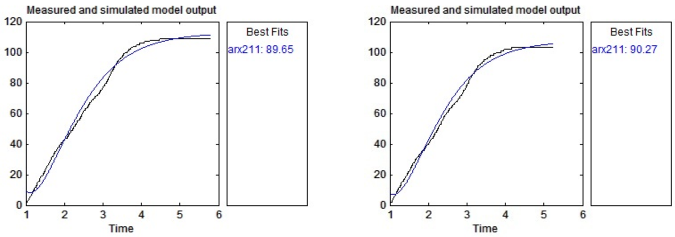
Training phase: in this phase, we applied the standard samples (objects) to identify the standard group parameter. In this phase, the arbitrary force command was applied to the gripper and the input/output pair data were collected. To ensure the robustness of the model, the experiments were repeated 10 times for each object. When all data were recorded, the system identification was applied to find the parameters of each data set. Fig. 6 shows an example of input-output pair data. Signal data from the encoder of the motor and the force sensor are plotted in this figure.



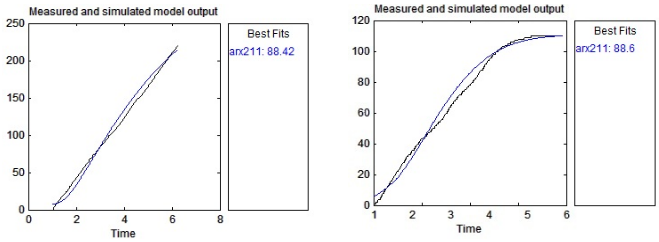
Force input Position output

Fig. 6. Example of input/output pair data

In our study, we configured the orders in ARX model as n_a = 2, n_b = 1, n_k = 1. This configuration makes the structure as shown in (2). By using the standard system identification, the model parameters, i.e., *m, b,* and *k* of each data set can be achieved. Examples of fitted data to verify the accuracy of identified model are shown in Fig. 7. As seen in this figure, more than 80% fitting accuracy of the model can be achieved.



(a) (b)



(c) (d)

Fig. 7 Best fit of the identification process for 4 objects.

The parameters of four types of objects from all experiments are shown in the appendix of this paper. The classification results of all test data are shown in the following table. As seen in this table, the object is identified correctly.

Table 1: Classification results from K-means and identified parameters.

Group / Sample No.	A	B	C	D
1	3	2	4	1
2	3	2	4	1
3	3	2	4	1
4	3	2	4	1
5	3	2	4	1
6	3	2	4	1
7	3	2	4	1
8	3	2	4	1
9	3	2	4	1
10	3	2	4	1

The following figure shows the plot of all data from the identification process. As seen in this figure, the data are grouped into 4 groups which each group has 10 sets of data. Clearly, the means from K-means can classify the group of industrial cans. The axes represent the value of mass, spring and damper.

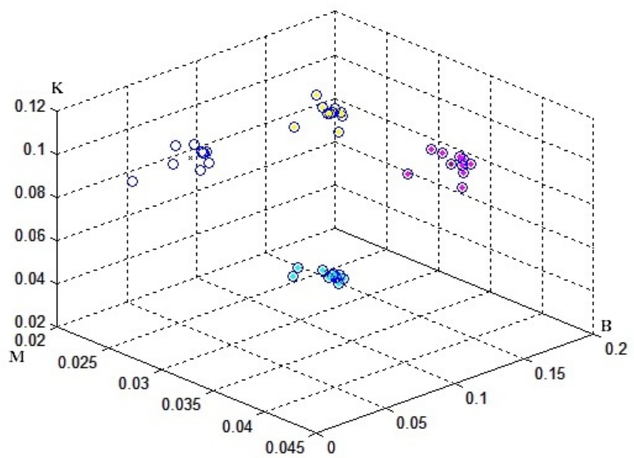


Fig. 8 Scattering plots of mechanical parameters of the objects.

Testing or operating phase: In this period, we applied the other samples of pre-defined objects. 30 samples were applied to the proposed gripper for ensuring the effectiveness of the our developed system. The percentage of accuracy of the classification is 100%.

IV. CONCLUSIONS

As seen in the experimental results, the classification of the grasped object using the developed smart gripper is feasible. By combining the system identification and K-mean clustering method, the classification of the commercial cans can be achieved. In our results, the model of ARX is used as the standard model and the accuracy of identified model is between 84% - 92.08%; these results verify the effectiveness of the proposed system identification using the sensor data. As seen in scattering data in Fig. 8, the mechanical properties of each object type are significantly different. By applying the K-mean clustering, the groups of the objects can be classified correctly. Future work is using Kohonen's network approach.

APPENDIX

Table A.1 Parameters and % best fit of the object type A.

No.	*m*	*b*	*k*	Best fit
1	0.036819	0.126951	0.095066	89.65
2	0.040096	0.139646	0.106474	91.44
3	0.037187	0.140916	0.103622	88.75
4	0.040501	0.139519	0.099819	85.17
5	0.040869	0.142185	0.103812	88.93
6	0.040501	0.138377	0.103527	88.66
7	0.041237	0.133299	0.096017	90.54
8	0.040133	0.142185	0.104573	91.44
9	0.03866	0.138377	0.105523	86.96
10	0.040206	0.133299	0.104478	89.56

Table A.2 Parameters and % best fit of the object type B.

No.	*m*	*b*	*k*	Best fit
1	0.027056	0.117505	0.09954	90.27
2	0.029762	0.131606	0.108399	92.07
3	0.030032	0.12808	0.100535	89.37
4	0.029735	0.12338	0.109494	85.75
5	0.029545	0.128315	0.110489	89.54
6	0.029464	0.127963	0.108698	89.27
7	0.027327	0.131606	0.111485	91.17
8	0.030303	0.12808	0.108499	92.08
9	0.029491	0.12338	0.109494	87.56
10	0.028409	0.128315	0.108698	90.18

Table A.3 Parameters and % best fit of the object type C.

No.	m	b	k	Best fit
1	0.027964	0.110291	0.033893	88.42
2	0.03076	0.123526	0.036909	90.19
3	0.03104	0.120217	0.034232	87.53
4	0.030732	0.115806	0.037282	83.99
5	0.030537	0.120438	0.037621	87.71
6	0.030453	0.120107	0.037282	87.44
7	0.028244	0.111394	0.03796	89.30
8	0.03132	0.12132	0.036943	90.19
9	0.030481	0.122423	0.035588	85.76
10	0.029362	0.12121	0.037011	88.33

Table A.4 Parameters and % best fit of the object type D.

No.	m	b	k	Best fit
1	0.021617	0.07099	0.082231	88.6
2	0.024211	0.078089	0.086343	90.37
3	0.023563	0.078799	0.089796	87.71
4	0.022698	0.078018	0.092099	84.17
5	0.023606	0.077521	0.089632	87.89
6	0.023541	0.077308	0.090454	87.62
7	0.021833	0.0717	0.091276	89.48
8	0.023779	0.079509	0.090372	90.37
9	0.023995	0.077379	0.08955	85.94
10	0.023757	0.07454	0.083053	88.51

ACKNOWLEDGMENT

This work was supported by CALComp Company and DSTAR.

REFERENCES

[1] S. E.M. Jansen, W. M. Bergmann Tiest, and A. M.L. Kappers, "Identifying Haptic Exploratory Procedures by Analyzing Hand Dynamics and Contact Force," *IEEE Trans. on Haptics*, vol. 6, no. 4, October-December 2013.

[2] H. Liu, X. Song, J. Bimbo, L. Seneviratne and K. Althoefer, "Surface Material Recognition through Haptic Exploration using an Intelligent Contact Sensing Finger," *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, October 7-12, 2012. Vilamoura, Algarve, Portugal

[3] M. A. Hoepflinger, C. D. Remy, M. Hutter, L. Spinello, and R. Siegwart, "Haptic Terrain Classification for Legged Robots," *2010 IEEE International Conference on Robotics and Automation Anchorage Convention District*, May 3-8, 2010, Anchorage, Alaska, USA

[4] G.Vásárhelyi, M. Ádám, Cs.Dücso, I. Bársony, A. Kis, "Integrated Tactile System for Dynamic 3D Contact Force Mapping", *Sensors, 2008 IEEE*, 26-29 October 2008.

[5] F. B. Carbajal, G. S.-Navarro, B. V.-Gonzalez, "Active Vibration Absorption of Multi-Frequency Harmonic Forces on Mass-Spring-Damper Systems," *Electrical Engineering Computing Science and Automatic Control (CCE), 2011 8th International Conference on*, 26-28 October 2011

[6] I. Ladipo, A. G.A. Muthalif, A. Rozaime, A. Asyraf, "Design and development of an active mass damper for boardband vibration control," *14th International Conference on Mechatronics (ICOM)*, 17-19 May 2011, Kuala Lumpur, Malaysia

[7] B. B. Mnyazikwiye, H. R. Karimi, K. G. Robbersmyr, "Mathematical Modeling of Vehicle Frontal Crash by a Double Spring-Mass-Damper Model," *2013 XXIV International Conference on Information, Communication and Automation Technologies (ICAT)*, October 30 – November 01, 2013, Sarajevo, Bosnia and Herzegovina

[8] K.-Y. Chen, M.-S. Huang, R-F. Fung, "The comparisons of minimum-energy control of the Mass-Spring-Damper system," *Proceedings of the 8th World Congress on Intelligent Control and Automation*, June 21-25 2011, Taipei, Taiwan

[9] Z. X.-ping, Q. Z. Hong, C. Yu-shu, L. Sheng-chun, "Research on the Power and Anti-vibration Characteristics of Damper," *Power Engineering and Automation Conference (PEAM), 2011 IEEE,* vol. 3 , 8-9 Sept. 2011

[10] W. Cai, S. Chen, and D. Zhang, "A Multiobjective Simultaneous Learning Framework for Clustering and Classification," *IEEE Trans on Neural Networks*, vol. 21, no. 2, Feburary 2010.

[11] T. Bhattacharjee, J. M. Rehg, and C. C. Kemp, "Haptic Classification and Recognition of Objects Using a Tactile Sensing Forearm," *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, October 7-12 2012, Vilamoura, Algarve, Portugal.

[12] D. S. Chathuranga, V. A. Ho and S. Hirai, "Investigation of a Biomimetic Fingertip's Ability to Discriminate Fabrics Based on Surface Textures," *Advanced Intelligent Mechatronics (AIM), 2013 IEEE/ASME International Conference on*, July 9-12 2013, Wollongong, NSW, Australia.

[13] D. S. Chathuranga, Z. W. V. A. Ho, A. Mitani, and S. Hirai, "A Biomimetic Soft Fingertip Applicable to Haptic Feedback Systems for Texture Identification," *A Biomimetic Soft Fingertip Applicable to Haptic Feedback Systems for Texture Identification*, October 26-27 2013, Istanbul.

[14] H. Yussof and M. Ohka, "Application of Stiffness Control Algorithm for Dexterous Robot Grasping using Optical Three-Axis Tactile Sensor System," *Haptic Audio Visual Environments and Games (HAVE), 2013 IEEE International Symposium on*, Nov. 9-11 2009, Istanbul

[15] A. Drimus and G. Kootstra, Arne Bilberg and Danica Kragic, "Classification of Rigid and Deformable Objects Using a Novel Tactile Sensor," *Advanced Robotics (ICAR), 2011 15th International Conference on*, June 20-23 2011, Tallinn University of Technology, Tallinn, Estonia.

[16] M. Shibata and S. Hirai, "Soft object manipulation by simultaneous control of motion and deformation," *Robotics and Automation, 2006. ICRA 2006. Proceedings 2006 IEEE International Conference on*, May 15-19 2006, Orlando, Florida.

[17] L. Jung, *System Identification: Theory for the User*, 2nd edition. New Jersey: Prentice-Hall; 1999.