Fuzzy Classification of Contact Formations from Sensor Patterns *

Marjorie Skubic and Richard A. Volz

Department of Computer Science
Texas A&M University
College Station, TX 77843-3112

Abstract

This paper presents a pattern recognition approach to identifying contact formations from force sensor signals. The approach is sensor-based and does not use geometric models of the workpieces. The design of a fuzzy classifier is described, where membership functions are generated automatically from training data. The technique is demonstrated using supervised learning. Test results are included for experiments using both rigid and non-rigid workpieces. The technique is discussed in the context of robot programming by human demonstration.

1 Introduction

Robot programming by using human demonstration has become an active research area. The method provides a natural approach to human-robot interaction and at the same time, avoids much of the computational complexity found in model-based program generation. Vision-based systems have been proposed and developed, which strive to extract an assembly plan from human demonstrators [10, 5]. While useful for observing high-level task information, vision has so far not proven adequate for observing intricate assembly operations. Capabilities could be expanded with the use of force-based skills.

While not yet coupled with vision, force signals have been incorporated into programming by demonstration (PbD) systems, to learn compliant task strategies for assembly operations (e.g., [2, 1]). Although progress has been made, the methodology has thus far been restricted to using simple workpieces and limited motions, such as no rotational movement.

An approach to assembly operations which we believe can be combined with robot PbD is to model the assembly task as a sequence of discrete states, representing the contact formations (i.e., contact state) between workpieces. In this way, the learning process can be simplified and the learned program should be more robust to discrepancies in position and orientation. The utility of this approach was demonstrated in [7]. However, the current methods used to identify the discrete contact states require a geometric model of the workpieces (e.g., [4, 6] and often ignore uncertainty and friction.

In this paper, we present a sensor-based scheme for identifying contact formations which does not use geometric models of the workpieces. In contrast to the method used in [8], our method is based on a quasi-static contact condition. Similar to the approach used in [3], our method uses fuzzy logic to model and recognize the sensory patterns and also resolve the inherent ambiguities. In addition to its pattern recognition strengths, fuzzy logic provides a linguistic interface to the human demonstrator, which makes it particularly well-suited to the PbD method. We believe this will provide a natural method for transferring force-based assembly skills from human experts to robots.

2 Learning Sensory Patterns of Contact Formations

The contact formation (CF) provides a qualitative description of how 2 or more objects make contact with each other (e.g., vertex to surface, edge to edge). As such, the possible CFs depend on the relative size and shapes of the objects, reflecting the geometric relationship.

To accomodate the need for identifying CFs from sensory data only, we first collected training data while in known contact states. To accomplish this, training data was collected while the robot and a grasped workpiece were kept stationary and the environment was moved manually. A 6 degree of freedom force sensor was attached to the robot arm for measuring force and moment vectors. It was assumed that the robot was grasping a workpiece in a consistent orientation, so that the force and moment patterns could be investigated. In this manner, controlled contact conditions were relatively easy to maintain. The sensory patterns were then learned from the training data and encapsulated in a form that can be used later for automatic program generation as well as for control during program execution.

2.1 Contact Formation Patterns

The set of force and moment vectors that comprise all possible vectors for a given CF form a cone [4], which reflects the motion constraints existing between

*This work has been supported by NSF under grants CDA-9115123, CDA-9422123, and EID-9017249 and by the State of Texas under TATP grants 999903-267 and 999903-095.

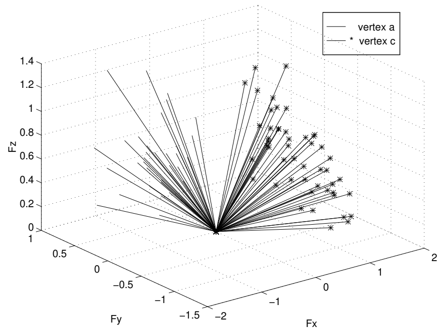

Figure 1: **Force Vector Patterns for Two Vertex Contact Formations**

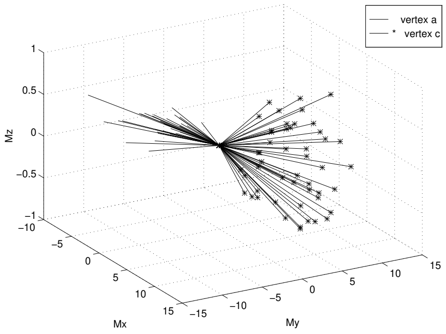

Figure 2: **Moment Vector Patterns for Two Vertex Contact Formations**

the objects in a given CF. Figures 1 and 2 shows example force and moment patterns for several measurements on 2 vertex-to-surface contact formations. This data was collected using a small plastic block in contact with a flat plate. Unlike a machined aluminum block, this plastic block does not have sharp edges, and the bottom surface has a texture. Even with these imperfections, the CF force and moment vectors formed distinct patterns.

2.2 A Fuzzy Classifier

A classifier can be constructed and used to identify the CF, based on the force and moment sensory patterns. Each class represents a unique CF. An example is the classifier developed by Hirai et al, which uses a geometric model to build polyhedral convex cones that approximate the sensory patterns [4]. We propose, as a sensor-based pattern classifier, the use of fuzzy logic. Empirical training data, instead of geometric models, is used to learn the sensory patterns. Fuzzy membership functions are used to represent the patterns.

In order to build a classifier, one or more features must be identified which can be used to distinguish between different CF's. As shown in Figure 1, one significant feature is the direction of the vector. Preprocessing is used to normalize the data vectors, yielding a projection on a unit sphere which indicates the direction.

Our classifier is structured as one logical rule per class, which describes the mapping between sensory data and CF. Each rule is implemented using all 6 normalized sensor signals as features for the classifier. The set of possible signals for each feature is represented as a fuzzy membership function. Let f_x, f_y, and f_z be the normalized force components of the sensor signal, and m_x, m_y, and m_z be the normalized moment components. The corresponding membership functions for contact formation C_i are represented by Fx_i, Fy_i, Fz_i, Mx_i, My_i, and Mz_i. Membership functions are combined using a fuzzy conjunction operator. Each rule has the following form:

$$\begin{array}{ll} \text{if} & f_x \text{ is } Fx_i \text{ and} \\ & f_y \text{ is } Fy_i \text{ and} \\ & f_z \text{ is } Fz_i \text{ and} \\ & m_x \text{ is } Mx_i \text{ and} \\ & m_y \text{ is } My_i \text{ and} \\ & m_z \text{ is } Mz_i \\ \multicolumn{2}{l}{\text{then } \mathit{class} \text{ is } C_i} \end{array}$$

The membership functions are generated automatically using supervised learning. Training data is acquired by demonstrating each CF class and collecting the force and moment signals generated. In the training process, the operator attempts to cycle through the range of possible vectors for each CF.

For each class, the mean, μ, and standard deviation, σ, are calculated. These are used as parameters to generate the membership functions, $\pi(r)$, as shown:

$$\pi(r) = 1 - e^{-(3\sigma/|\mu - r|)^3}$$

This membership function shape was chosen as a means of modeling the sensor distribution, as well as allowing for uncertainties in the sensor signals. Figure 3 shows a representative sensor distribution with the corresponding scaled membership function generated, for a sample CF [1]

Two factors contribute to the range in possible force signals for a contact formation. The bigger factor is the way a workpiece can move and still maintain the desired contact formation. This is a function of the unconstrained degrees of freedom and the friction present. These movements will result in a change in the force components, but as long as the CF is maintained, any of the force signals will still be valid for that class. A smaller factor contributing to the range is the sensor uncertainty (noise). The membership function shape is designed so that the flat portion of the curve will encompass almost the complete range of signals, which models the effect of the first factor. As the curve drops off, this models the effect of the sensor uncertainty.

A fuzzy conjunction operator is also needed to combine the 6 membership functions. In this case, the Hamacher product is used in a reduced form as shown:

$$H_n = \frac{1}{\sum_{i=1}^{n} \frac{1}{\pi_i} - (n-1)}$$

[1] The actual membership function would have a maximum value of 1.

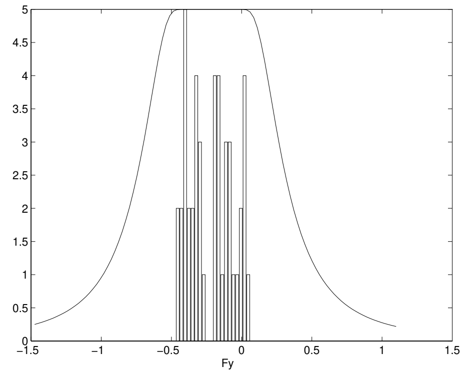

Figure 3: **The Distribution of the Edge 2 (Fy) Training Data Is Shown with the Generated Membership Function**

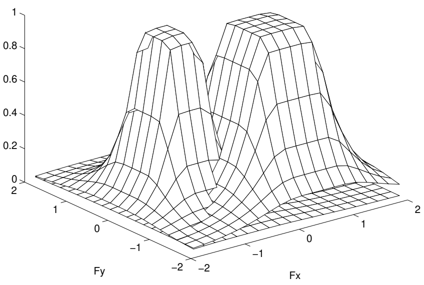

Figure 4: **The Combination of Two Membership Functions for Vertex a (left) and Vertex c (right)**

where n is the number of membership functions to be combined. See [9] for more details.

The combination of the 6 feature membership functions is interpreted as the possibility (i.e., a fuzzy number in [0,1]) of this sensor data set being in the specified class. Possibility values are calculated for each class; the highest possibility number represents the identified CF class. A threshold is also used to determine whether any classification can be made (empirically set to 0.2). If no possibility value is above the threshold, then the data vector is said to be unclassified.

The effects of the combination can be seen in Figures 4 and 5, where only 2 of the features are combined. Although these are partial combinations, the distinct shapes are apparent, showing how an edge pattern compares to a vertex pattern.

3 Experiments

Experiments were conducted using an American Robot Merlin robot arm with an attached JR3 force sensor. Force signals were logged at a low frequency (2 Hz). The training data and test data was acquired

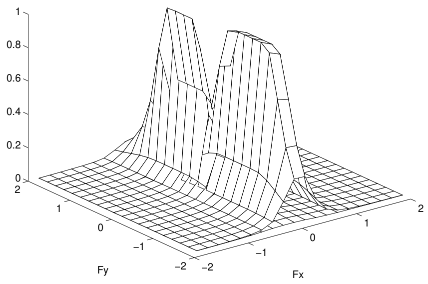

Figure 5: **The Combination of Two Membership Functions for Edge 1 (left) and Edge 3 (right)**

with the robot stationary and an operator moving the environment.

3.1 Classifier Results

Three tests are described here; the results are summarized in Table 1. More test results are given in [9]. The first test used a square plastic block with 12 CF classes. Each CF consisted of a specified portion of the block making contact with a planar surface (the environment). The success ratio was 94%.

Test 2 used a pentagon-shaped plastic block. As before, each contact formation consisted of a specified portion of the block making contact with a planar surface (the environment). In all, 21 CF classes were used, consisting of 5 vertex, 10 edge, and 6 surface-to-surface CF's. As shown in Table 1, the success ratio was 84%. The lower success ratio reflects the sheer volume of classes and the tight proximity between classes in the feature space.

In Test 3, we used a real-world, 3-pronged power plug. The plug differs from the blocks, in that it is slightly flexible. The left and right metal tines can flex in and out. In addition, the plug is attached to a slightly flexible tube, allowing the plug to rotate slightly along the vertical axis. In this test, the environment is a 3-holed power strip. Seven CF classes are used, specifying how the plug contacts the holes in the power strip: (1) center prong, (2) left prong, (3) right prong, (4) left and right prongs, (5) left and center prongs, (6) right and center prongs, and (7) all 3 prongs. The success ratio for Test 3 is 95%.

3.2 Discussion

In the experiments presented, the intention was to create a controlled setting so that the initial training data would be as clean as possible (i.e., vectors from one CF only). Ultimately, we hope to use the technique in demonstrating a sequence of contact formations. Eventually, unsupervised training may be used. Instead of demonstrating each CF class individually, the operator would demonstrate the sequence. Clustering and/or task segmentation would be used to separate the vectors into different classes, thus generating the training data automatically,

Table 1: Classifier Results

Test	Training Set	Test Set	Classes	% Success	Good	Misses	Unclassified
1	Square block	Square block	12	93.9	459	30	0
2	Pentagon block	Pentagon block	21	83.9	774	148	0
3	Plug	Plug	7	95.3	346	16	1

Preliminary trials have been done to test the technique with a moving robot. A 6 degree-of-freedom hand controller (without force reflection) was used to drive the robot and make contact with a fixed environment. Translational movement was relatively easy to demonstrate, and the resulting CF's were relatively easy to detect.[2] However, manually driven rotational movement (while maintaining a constant CF) proved difficult to achieve without haptic feedback. In the future, we intend to use the commercially available *PHANToM* to provide haptic feedback during the demonstration process.

To increase the success of CF classification, we intend to combine our fuzzy classifier with other methods, such as that proposed by McCarragher [8]. Another idea is to add task context information, to help in resolving ambiguities. Task context could be provided in the form of a graph or petri net which holds the feasible sequences of CF's. Using fuzzy logic, the graph could allow the possibility of more than one CF and propagate this information through the graph.

4 Conclusions

The data and analysis presented in this paper are intended to provide a starting point for identifying contact formations without using geometric models. The goal is to provide a method for robot PbD, which supports rotational movement, as well as workpieces that are imperfect, asymmetrical, and flexible. The fuzzy classifier is only one possible pattern recognition approach. Other types of classifiers (e.g., statistical classifiers) may work equally well. The advantage, however, of using a fuzzy classifier is that it is a relatively simple technique that provides computational efficiency as well as a linguistic interface to the human operator.

References

[1] H. Asada and H. Izumi. Automatic program generation from teaching data for the hybrid control of robots. *IEEE Transactions on Robotics and Automation*, 5(2):166–173, April 1989.

[2] Nathan Delson and Harry West. Robot programming by human demonstration: Subtask compliance controller identification. In *Proceedings of the 1993 IEEE/RSJ International Conference on International Conference on Intelligent Robots and Systems*, pages 33–41, Yokohama, Japan, July 1993.

[3] K. Hara and R. Yokogawa. Recognition of state in peg-in-hole by fuzzy schema. *Journal of Advanced Automation Technology*, 4(3):134–139, 1992.

[4] Shinichi Hirai and Kazuaki Iwata. Recognition of contact state based on geometric model. In *Proceedings of the 1992 IEEE International Conference on Robotics and Automation*, pages 1507–1512, Nice, France, May 1992.

[5] S.B. Kang and K. Ikeuchi. Toward automatic robot instruction from perception– temporal segmentation of tasks from human hand motion. *IEEE Transactions on Robotics and Automation*, 11(5):670–681, October 1995.

[6] Kosei Kitagaki, Tsukasa Ogasawara, and Takashi Suehiro. Methods to detect contact state by force sensing in an edge mating task. In *Proceedings of the 1993 IEEE International Conference on Robotics and Automation*, volume 2, pages 701–706, Atlanta, GA, May 1993.

[7] Kazuhiro Kosuge, Toshio Fukuda, and Haruhiko Asada. Acquisition of human skills for robotic systems. In *Proceedings of the 1991 IEEE International Symposium on Intelligent Control*, pages 469–474, Arlington, VA, August 1991.

[8] Brenan J. McCarragher. Force sensing from human demonstration using a hybrid dynamical model and qualitative reasoning. In *Proceedings of the 1994 IEEE International Conference on Robotics and Automation*, volume 1, pages 557–563, San Diego, CA, May 1994.

[9] Marjorie Skubic and Richard A. Volz. Identifying contact formations from sensory patterns and its applicability to robot programming by demonstration. In *Proceedings of the 1996 IEEE/RSJ International Conference on International Conference on Intelligent Robots and Systems*, Osaka, Japan, November 1996.

[10] Y.Kuniyoshi, M. Inaba, and H. Inoue. Learning by watching: Extracting reusable task knowledge from visual observation of human performance. *IEEE Transactions on Robotics and Automation*, 10(6):799–822, December 1994.

[2] During the demonstration, visual feedback of force and moment data was provided to the operator in the form of a graphics display.