Identifying Contact Formations from Sensory Patterns and Its Applicability to Robot Programming by Demonstration *

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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. Several such programming systems have been proposed and developed.

Vision has been used by Kuniyoshi et al [13] and Kang and Ikeuchi [7] to observe and extract an assembly plan from human demonstrators. While useful for observing high-level task information, vision has so far has not proven adequate for observing intricate assembly operations. Capabilities of such vision systems 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 systems, in order to learn compliant task strategies for assembly operations (e.g., the work of Delson and West [2], Asada and Izumi [1], and Wang et al [12]). Much of this work concentrates on the low level servo control issues, attempting to learn the parameters for control functions that can be used for each subtask segment. Although progress has been made, the methodology has thus far been restricted to using simple workpieces and limited motions, such as no rotational movement.

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An approach to assembly operations which we believe can be combined with robot programming by demonstration is to model the assembly task as a sequence of discrete states, representing the contact formations (i.e., contact state) [3] 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 by Kosuge, Fukuda, and Asada in [9]. However, the current methods used to identify the discrete contact states require a geometric model of the workpieces (e.g., [6, 8, 4]. Often uncertainty and friction are ignored, and the process can still be complex for even simple workpieces. In addition, ambiguities may prevent the identification of the one correct contact formation.

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 by McCarragher in [10], our method is based on a quasi-static contact condition. Similar to the approach used in [5], 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 programming by demonstration method. We believe this will provide a natural method for transferring force-based assembly skills from human experts to robots.

In Section 2, the sensory patterns will be described and the design of a fuzzy classifier will be discussed. Section 3 will present experimental results, with discussion including how the technique might be used for robot programming by demonstration. Conclusions will be given in Section 4.

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 contact formations depend on the relative size and shapes of the objects, reflecting the geometric relationship. Our goal, however, is to

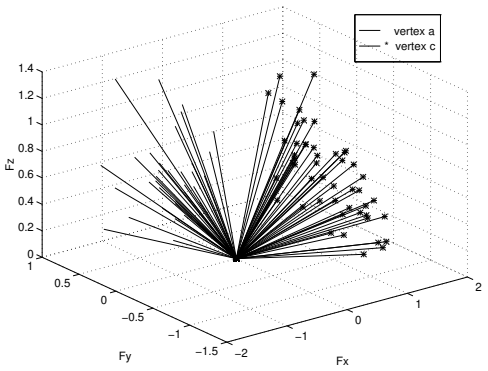

Figure 1: **Force Vector Patterns for Two Vertex Contact Formations**

recognize them from sensory data only, without using detailed geometric knowledge.

To accomodate the need for identifying contact formations 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, which reflects the motion constraints existing between the objects in a given CF. A theoretical discussion is provided by Hirai and Asada in [6]. Figures 1 and 2 show example force and moment patterns for several measurements on 2 vertex-to-surface contact formations. This data was collected using the block shown in Figure 3 in contact with a flat plate. This is a plastic toy block, with dimensions approximately 3 x 3 x 4 cm. 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

Because of the sensory patterns, a classifier can be constructed and used to identify the CF, based on the force and moment sensory data. Each class represents a unique CF. An example is the classifier developed by Hirai and Asada, which uses a geometric model to build polyhedral convex cones that approximate the sensory patterns [6]. We propose, as a sensor-based

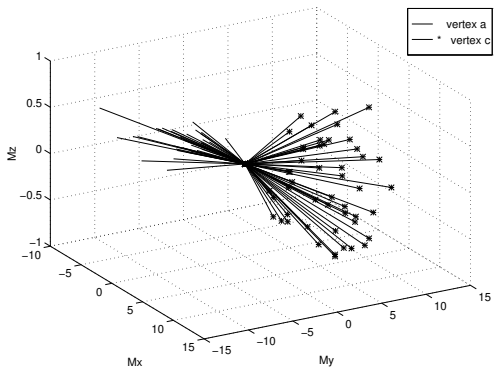

Figure 2: **Moment Vector Patterns for Two Vertex Contact Formations**

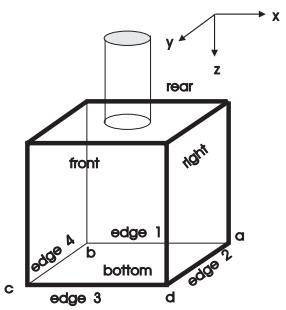

Figure 3: **Square Block Showing 12 Contact Formations**

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 Figures 1 and 2, one significant feature is the direction of the vector. Because its magnitude is not significant, 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 has the following form:

if *force* is F_i and
moment is M_i
then *class* is C_i

where *force* and *moment* are the measured vectors, and F_i and M_i are the set of possible force and moment vectors measured at contact formation C_i.

This logical rule is implemented as an expanded rule which uses all 6 normalized sensor signals as features for the classifier. The 6 normalized components of the force sensor provide a method of capturing the direction of the force and moment vectors. 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 are represented by Fx_i, Fy_i, Fz_i, Mx_i, My_i, and Mz_i. Fuzzy conditions about sensor signals are combined using a fuzzy conjunction operator. Each expanded rule has the following form:

if f_x is Fx_i and
f_y is Fy_i and
f_z is Fz_i and
m_x is Mx_i and
m_y is My_i and
m_z is Mz_i
then *class* is C_i

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. Because this is a manual process, it is difficult to achieve a perfect training set, where the training data contains the complete range of vectors for the desired CF and vectors from only one CF. However, the training data does not have to be perfect to be useful.

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 below:

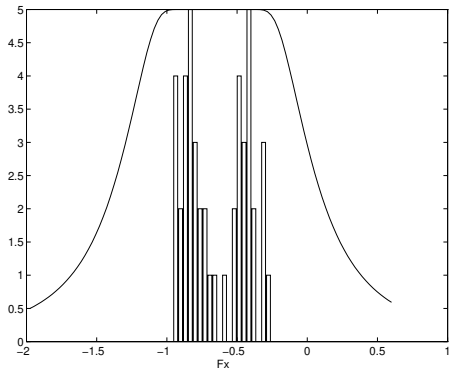

Figure 4: **The Distribution of the Edge 2 (Fx) Training Data Is Shown with the Generated Membership Function**

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

This membership function shape was chosen as a means of modeling the possible sensor distribution, as well as allowing for uncertainties in the sensor signals. Figures 4, 5, 6, 7, 8, and 9 show the distributions for each sensor component with the corresponding membership function generated, for a sample contact formation (the edge2-to-surface 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.

Returning to the structure of the expanded fuzzy rule, we can see that a fuzzy conjunction operator is needed to combine the 6 membership functions. In this case, the Hamacher product [14] is used. The Hamacher product is defined for 2 fuzzy sets, as shown below:

$$H(\pi_A(r), \pi_B(r)) = \frac{\pi_A(r) * \pi_B(r)}{\pi_A(r) + \pi_B(r) - \pi_A(r) * \pi_B(r)}$$

It can be used in an iterative fashion, until the membership functions of all 6 features are combined. [2]

[1] The membership functions shown are scaled to match the histogram. The actual membership functions have a maximum value of 1.

[2] The order in which the features are combined is irrelevent, as the Hamacher product follows the fuzzy t-norm requirements for commutativity and associativity.

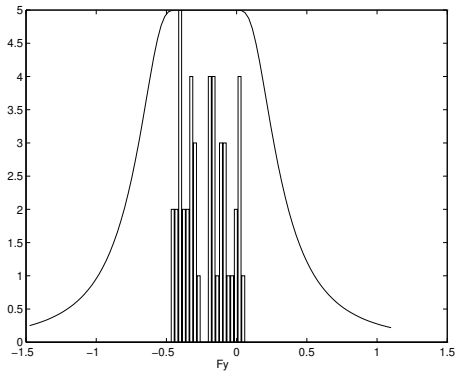

Figure 5: **The Distribution of the Edge 2 (Fy) Training Data Is Shown with the Generated Membership Function**

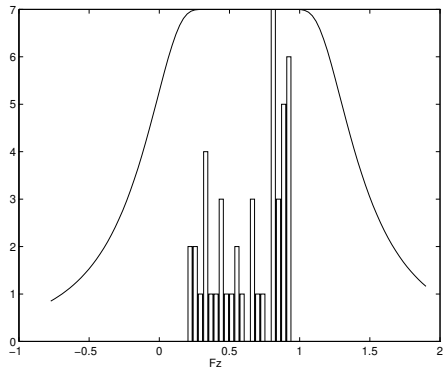

Figure 6: **The Distribution of the Edge 2 (Fz) Training Data Is Shown with the Generated Membership Function**

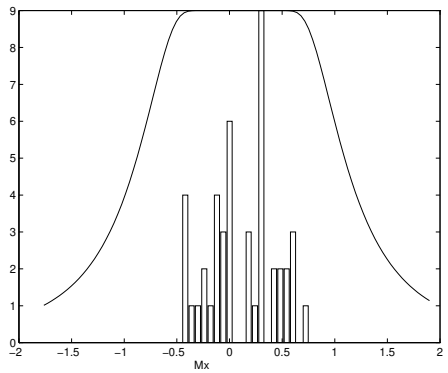

Figure 7: **The Distribution of the Edge 2 (Mx) Training Data Is Shown with the Generated Membership Function**

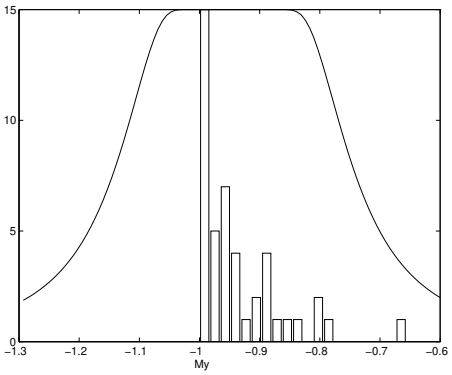

Figure 8: **The Distribution of the Edge 2 (My) Training Data Is Shown with the Generated Membership Function**

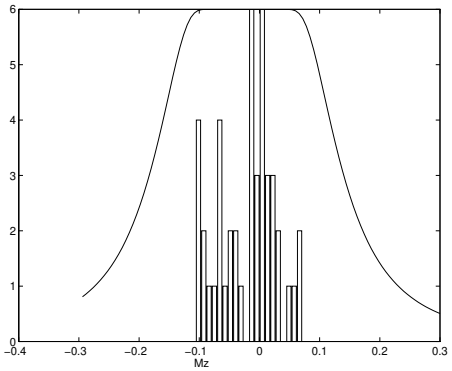

Figure 9: **The Distribution of the Edge 2 (Mz) Training Data Is Shown with the Generated Membership Function**

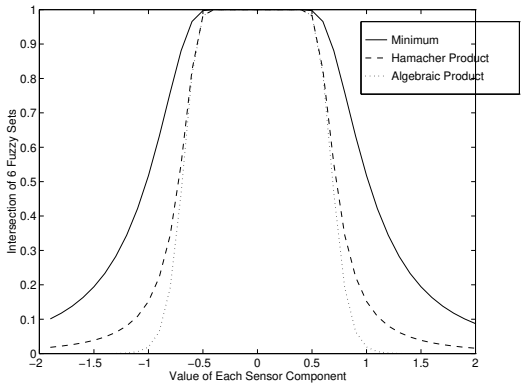

Figure 10: **A Comparison of 3 Conjunction Operators, Showing the Result of Combining 6 Identical Membership Functions.** The example shows a membership function with a mean of 0.0 and standard deviation of 0.3.

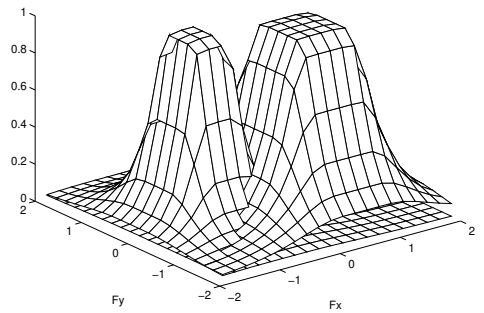

Figure 11: **The Combination of Two Membership Functions for Vertex a (left) and Vertex c (right)**

As an alternative, the Hamacher product can be reduced to the following form:

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

where n is the number of membership functions to be combined.

Other conjunction operators were investigated, including the minimum function and the algebraic product. The Hamacher product was ultimately chosen because it yielded the best combination of membership functions. Figure 10 shows the comparison of the 3 intersection operators, by plotting the resulting combination of 6 identical membership functions. The Hamacher and algebraic products drop off much faster than the minimum function, thereby providing better discrimination between classes which are close together in feature space. The Hamacher product broadens the combined function slightly more than the algebraic product. Empirical results have shown it to be slightly better than the algebraic product.

The combination of the 6 feature membership functions is then interpreted as the possibility (i.e., a fuzzy number in [0,1]) of this sensor data set being in the specified class. In the classification process, possibility values are calculated for each class; the highest possibility number represents the identified CF class. This has the effect of resolving classification ambiguities by selecting the class with the nearest prototype vector, which would be at the center of the combined fuzzy membership functions. In practice, a threshold is also used to determine whether any classification can be made. In the current tests, the threshold is 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 11 and 12, where only 2 of the features are combined. That is, this is a partial combination only.

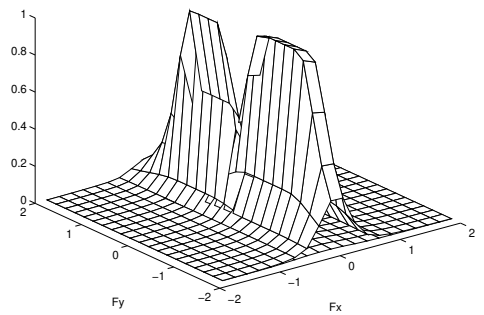

Figure 12: **The Combination of Two Membership Functions for Edge 1 (left) and Edge 3 (right)**

Still, the distinct shapes are apparent, showing how an edge pattern is shaped differently compared to a vertex pattern. From Figures 11 and 12, you can also see the effects of imperfect training data. Theoretically, the 2 vertex classes, and likewise the 2 edge classes, should have an identical shape.

3 Experiments

The experiments were conducted using equipment in the Texas A&M robotics lab, which is part of the USARC distributed robotics testbed [11]. An American Robot Merlin robot arm was used with an attached JR3 force sensor. Force signals were logged at a low frequency (2 Hz). To accomodate the robot's 3-pronged gripper, the test workpieces were fitted with a cylindrical handle. The training data and test data was acquired with the robot stationary and an operator moving the environment.

3.1 Classifier Results

Five tests were performed, the results being summarized in Table 1. The first 3 tests used the square

plastic block shown in Figure 3. Twelve CF classes were used on the block, as shown. Each CF consisted of a specified portion of the block making contact with a planar surface (the environment). Test 1 was done with the robot in the home position and the arm power off. Test 2 was done in the same position but with the robot arm power on. In both cases, the success ratio was about 94%. Test 3 used the Test 1 training set (with arm power off) and tested against the Test 2 data (with arm power on). As expected, the success ratio decreased, to about 88%. This was expected, especially considering that the arm power contributes vibrations that affect the force sensor signals.

Test 4 used a pentagon-shaped plastic block, approximately 4 x 4 x 4 cm. 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 about 84%. The lower success ratio reflects the sheer volume of classes and the tight proximity between classes in the feature space.

In Test 5, we move beyond toy blocks and use a real-world, 3-pronged power plug. The plug also 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 flexible tube, allowing the plug to rotate slightly along the vertical axis. The length from tip to tip is approximately 10 cm. In this test, the environment is a 3-holed power strip. Seven CF classes are used, as shown below, 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
7. All 3 prongs

The classes chosen do not necessarily represent the entire range of possible contact formations but are typical CF's that might be encountered as the plug is inserted into the power strip. As shown in Table 1, the success ratio for Test 5 is 95%.

3.2 Discussion

The experiments presented here used a rather crude method of collecting training data sets. However, 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). Even so, it is still possible to create an undesired contact formation during the attempted demonstration of a single CF, especially if the operator is expected to cycle the workpiece through a range of possible vectors. One method of dealing with this problem would be to preprocess the training sets using a clustering algorithm. This would result in better training data.

Ultimately, we hope to use the technique in demonstrating a sequence of contact formations. Eventually, unsupervised training may be used. That is, 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,

A few preliminary trials were 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.[3] 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 the event-based approach proposed by McCarragher [10]. An event is defined as the change in contact formation, which can be recognized by monitoring the force signals. A sudden change in any of the force components indicates that an event has occurred, resulting in a loss or gain of contact. When such an event is detected, the fuzzy classifier can be run to identify the new contact formation. Preliminary tests have been done using this approach, and the results are promising.

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 captures knowledge about 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 programming by demonstration, 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.

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

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	Square (arm power)	Square (arm power)	12	94.5	496	29	0
3	Square block	Square (arm power)	12	87.6	460	65	0
4	Pentagon block	Pentagon block	21	83.9	774	148	0
5	Plug	Plug	7	95.3	346	16	1

The initial results, using a static robot and a moveable environment, are encouraging. The results were surprisingly good for the flexible plug. This may be explained by the relatively small number of classes and the fact that motion was quite restricted in the contact formations used with this test piece. We would not expect such good results in a task demonstration which may use a greater variety of CF's. Yet, this does show promise in using this technique for non-rigid parts.

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