Identifying Contact Formations from Force Signals: A Comparison of Fuzzy and Neural Network Classifiers *

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Abstract

In this paper, we present and compare two methods of identifying single-ended contact formations from force sensor patterns. Instead of using geometric models of the workpieces, both methods use force sensor signals only. In the first method, fuzzy logic is used to model the patterns in the force signals. Membership functions are generated automatically from training data and then used by the fuzzy classifier. In the second method, a neural network architecture is used to learn the mapping from force signals to contact formation class. Experimental results are presented for both the fuzzy and neural network classifiers, and the results are compared. In some cases, the fuzzy classifier has better performance, and in other cases, the neural net classifier is better. The results are discussed, and, finally, a training modification is presented which dramatically improves the performance of the inadequate neural net classifiers.

1. Introduction

The motivation behind this work is to transfer force-based assembly skills to robots by using human demonstration. Robot programming by demonstration 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. For this purpose, we model the skills as a sequence of discrete states, representing the contact formations (i.e., contact state) [2] between workpieces. In this way, the learning process is simplified and the learned program should be more robust to discrepancies in position and orientation. With this in mind, we must find a method of identifying the contact formation (CF) from the force signals only, without using geometric models of the workpieces.

Several approaches have been tried. McCarragher has used the discrete event approach to assembly, incorporating system dynamics and qualitative reasoning [7]. In [6], FFT's are used to identify contact states; however, this approach cannot easily be run in real-time. Hara and Yokogawa have used fuzzy logic to recognize the CF from force signals; however, only a small number of states for one case was considered [4].

Asada proposed the use of a neural network to learn the nonlinear mapping of forces to velocity commands [1]. Although it was not used for an output, a hidden layer was designed to identify the CF. This neural network approach was implemented by Whalen but was not found to be successful when extracting velocity commands from human demonstrated data [9]. However, since the CF was hidden within the network, we do not know whether his neural network successfully identified the CF class.

The focus of this paper will be on classifying the contact formations from force signals, without using geometric models. We will utilize our previous work [8], which is based on fuzzy logic, and also present a second approach using neural networks. The two classifiers will be compared by examining results on several

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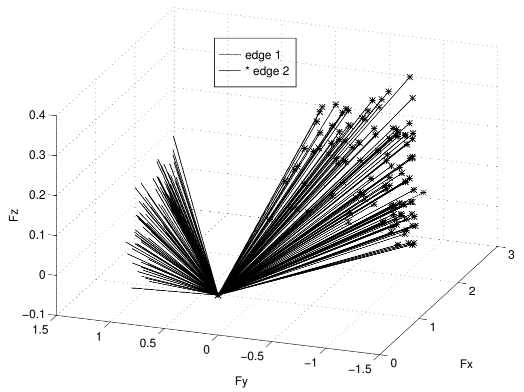

Figure 1. Force Vector Patterns for Two Edge Contact Formations

training sets. In Section 2, the sensory patterns of single-ended contact formations will be discussed. In Sections 3 and 4, the structure of the fuzzy and neural net classifiers will be presented. Section 5 will present experimental results, discussion, and a modified training method for the neural net classifier. Conclusions will be given in Section 6.

2. Sensory Patterns of Single-Ended Contact Formations

The single-ended contact formation (SECF) provides a qualitative description of how a grasped object makes contact with its environment (e.g., edge 1 of the object touches a side in the environment). Our goal is to recognize the SECF from force sensor data only, without using geometric knowledge or position information. For this purpose, we examine force sensor data, looking for distiguishable features.

The set of force and moment vectors that comprise all possible vectors for a given SECF form a cone, which reflects the motion constraints existing between the grasped object and its environment. A theoretical discussion is provided by Hirai and Asada in [5]. Figure 1 shows example force patterns for several measurements on 2 SECF's. Moment vectors yield a similar cone-shaped pattern. As illustrated in Figure 1, one significant feature is the direction of the vector. To capture the direction, preprocessing is used to normalize the data vectors. This yields a projection onto a unit sphere which indicates the direction. These normalized force and moment components are then used as inputs to both the fuzzy classifier and the neural net classifier.

3. The Fuzzy Classifier

Our fuzzy classifier is structured as one logical rule per class, which describes the mapping between sensory data and SECF. The 6 normalized sensor signals are used as features for the classifier, providing 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 for class C_i 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 rule has the following form:

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

The membership functions are generated automatically using supervised learning. Training data is acquired by demonstrating each SECF class and collecting the force and moment signals generated. For each class, the mean, μ, and standard deviation, σ, are calculated. These are used as parameters to generate the membership functions, $\pi(r) = 1 - e^{-(3\sigma/|\mu - r|)^3}$.

A fuzzy conjunction operator is used to combine the 6 membership functions. In this case, the Hamacher product is used in its reduced form [8]. 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. 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 0.5. If no possibility value is above the threshold, then the data vector is said to be unclassified. Please refer to [8] for more details and classification results.

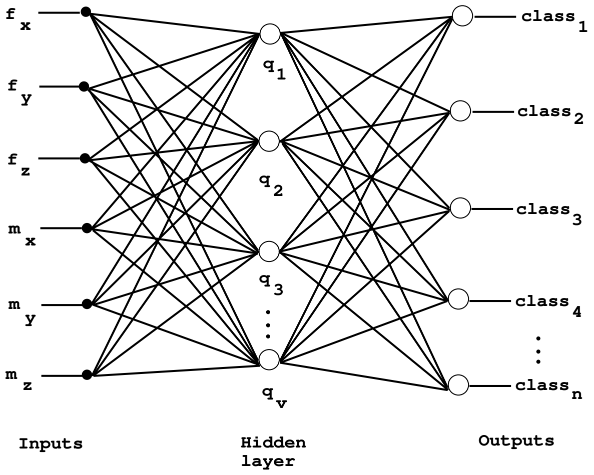

Figure 2. The Generalized Architecture for n classes and v vertices

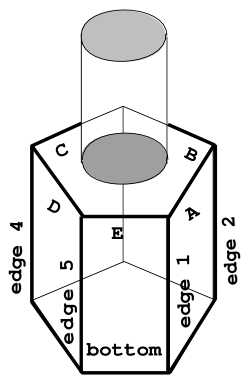

Figure 3. Pentagon Block with 11 Contact Formations: 5 sides, 5 edges plus the bottom surface (using 10 vertices)

4. The Neural Network Classifier

Our neural net classifier uses part of the network structure proposed by Asada for mapping force signals to velocity commands [1]. The generalized architecture is shown in Figure 2. The 6 input signals are the normalized components of the force and moment vectors. The number of output nodes is the number of contact formation classes to be identified. The values at the output nodes may be interpreted as confidence factors for each class. The highest confidence factor represents the identified class. As with the fuzzy classifier, a threshold is used to determine whether the input vector is unclassified.

The number of hidden nodes is dependent on the geometric shape of the object. There is one hidden node for each vertex on the object that is part of an included contact formation. That is, each vertex that can make contact with the environment, as part of the CF set, has a corresponding hidden node in the network. For example, one of our training sets contains 11 CF's using the pentagon-shaped block shown in Figure 3 (5 sides, 5 edges, and the bottom surface). Within those 11 CF's, there are 10 vertices that can make contact with the environment; therefore, the corresponding network would have 10 hidden nodes.

It is important to note that the network structure has physical meaning. The connections between the 6 input signals and the hidden nodes corresponds physically to the forces exerted on the object's vertex points. The final layer then maps the vertex points to the corresponding contact formation classes, thus providing the desired classification.

Training of the neural network was accomplished by using backpropagation with a constant learning rate (lr) [3]. The bipolar sigmoid was used as the activation function for both the hidden and output nodes. Training continued until the total squared error (tse) established an increasing instead of decreasing pattern. At that point, the training was stopped. The final weights and biases used for classification were those with the smallest tse encountered throughout the training process. The program used to train the neural network was written by the authors.

5. Experiments

To test the performance of the classifiers, experiments were conducted in the Texas A&M robotics lab. Training data was generated by demonstrating a known contact formation and monitoring the signals from a force sensor. The object was held in a fixed grasp by a robot arm. A JR3 force sensor mounted on the arm provided the force signals. For each set collected, the data were separated into 2 groups, one used for training the classifiers and the second used for testing.

The demonstration of a contact formation was done in one of 2 ways: (1) the robot arm was held in a fixed position and a human assistant manipulated the environment so that contact was made, or (2) the robot arm was driven by a teleoperator so that the grasped object made contact with the environment. In the second case, the PHANToM haptic device was used as a handcontroller so that haptic feedback was provided to the operator. In both demonstration modes, it was quite possible to collect data from an undesired CF, thus generating a kind of noise. Although every effort was made to collect clean data, undoubtedly some of this noise was included in the training sets.

5.1. Training Sets

Five sets of training data were used in our experiments, representing different shapes of objects and different combinations of CF classes. The training sets are characterized below:

- The *pentagon* set contains 11 classes and was made using the plastic, pentagon-shaped block shown in Figure 3. The set contains 6 surface and 5 edge CF's.

- The *plug* set was made using a slightly flexible 3-prong electrical plug. The 7 classes of CF's included the 7 combinations of single, double, and triple prongs, making contact against a flat surface.

- The *peg(11)* set was made using a 4-sided aluminum peg. The 11 classes included the bottom and 4 side surfaces and the 4 bottom edges. Two additional CF's were created by jamming the peg against 2 opposing inside surfaces of a hole.

- The *peg(9)* set was also made with the aluminum peg. The 9 classes included the bottom surface, 4 side surfaces, and 4 double-sided combinations (front and left, front and right, rear and left, rear and right).

- The *square* set was made using a small, plastic, square block. The 17 classes included the bottom and 4 side surfaces, 8 double-sided combinations, and the 4 bottom corner surface combinations.

5.2. Results

Results of the fuzzy and neural net classifiers are shown in Tables 1 and 2. To better understand the results, an interactive visualization program was written to analyze the data sets and observe whether the input vectors overlapped from one CF class to another. For the pentagon set, where no overlap was observed, both the fuzzy and neural net classifiers performed quite well. In the plug set, we observed almost no overlap; however, there were a few vectors that looked misplaced, probably as a result of the training-generated noise discussed earlier. These few inaccurate input vectors apparently did not impact the classification abilities of the neural net classifier. However, they may have decreased the success rate of the fuzzy classifier because of the small training size.

In the remaining 3 training sets, there was overlap in the input vectors. The peg(11) and square sets contained significant overlap or very close sets between some pairs of CF classes. This may explain the rather poor performance of the neural net classifier. The fuzzy classifier is not as sensitive to overlapping input sets, because membership functions are based strictly on the means and standard deviations of the input vectors. The peg(9) set contained some overlap between input vector sets but not as significant as the other 2 sets.

5.3. Modified Training of Neural Net Classifiers

In an effort to improve the performance of the neural net classifier for the peg and square training sets, we looked at alternative training methods. The attempts included adjusting the learning rate, using an adaptive learning rate, and using the Nguyen-Widrow initialization of weights [3]. None of these methods yielded significantly-improved results.

As a result, a two-step training process was developed. First, the classifier was trained using a small set of prototype vectors. For each CF class, 10 prototype vectors were generated using the means and standard deviations of the 6 input features for that class. Each generated prototype vector was within a range of 1 standard deviation of the mean for that class. This resulted in clean data with a well-defined separation between the sets of input vectors. The weights and biases learned by the network using the prototype vectors were saved and then used as starting weights and biases for the second phase of training. In the second phase, the complete training set was used to train the neural net.

The results of the 2-step training process are shown in Table 3. The modified training process yielded dramatically improved classification results. The success rates for all of the classifiers and sets are summarized in Figure 4.

6. Conclusion

In this paper, we addressed the problem of identifying single-ended contact formations from force signals, without using geometric information. Two classifiers were presented. The first, based on fuzzy logic, used membership functions that were generated automatically from training data. The second used a neural network and backpropagation algorithm to learn the mapping from force signals to CF class.

The classifiers were tested using 5 training sets generated in our robotics lab. Both classifiers performed

Table 1. Fuzzy Classifier Results

Set	Classes	good	misses	unclass.	success rate
pentagon	11	1822	15	8	98.8
plug	7	168	5	6	93.9
peg(11)	11	1333	82	6	93.8
peg(9)	9	3354	204	26	93.6
square	17	8233	52	166	97.4

Table 2. Neural Net Classifier Results

Set	Classes	Hidden	tse	epochs	lr	good	misses	unclass.	success rate
pentagon	11	10	9.5	766	0.1	1818	11	16	98.5
plug	7	3	12.0	13000	0.2	177	1	1	98.9
peg(11)	11	8	103	600	0.1	1119	192	110	78.7
peg(9)	9	8	152	65300	0.1	3277	53	254	91.4
square	17	8	212	200	0.1	6250	833	1368	74.0

Table 3. Modified NN Classifier Results

Set	Classes	Hidden	tse	epochs	lr	good	misses	unclass.	success rate
peg(11)	11	8	87	20100	0.025	1392	17	12	98.0
peg(9)	9	8	147	5900	0.050	3388	95	101	94.5
square	17	8	203	1200	0.050	8263	91	97	97.8

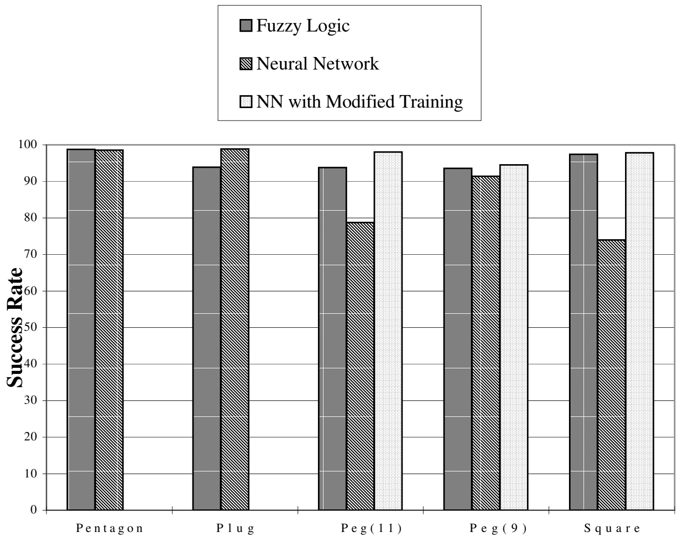

Figure 4. Classifier Performance Comparison

well when the sets of input vectors did not overlap between classes. On those sets where there was signficant overlap, the neural net classifier performed poorly. Although the performance was affected somewhat, the fuzzy classifier was not found to be as sensitive to overlap in the input data.

To improve the poorly-performing neural net classifiers, a two-step training process was introduced. A small set of prototype input vectors was generated so that there was a well-defined separation between classes. The network was first trained using the prototype vectors. The learned weights and biases were then used as a starting point for the second step where the entire training set was used. The modified training process yielded significantly-improved classification results.

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