Clustering of Qualitative Contact States for a Transmission Assembly

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Abstract

Current manufacturing methods for robotic-controlled assembly rely on accurate positioning to ensure task completion, often through the use of special fixtures and precise calibration of the workspace. The reliance on precision positioning to achieve proper alignment creates problems in both programming and control of contact-based tasks. As a means of addressing these problems, we have been investigating the use of qualitative contact states (QCS) for modeling and learning low-level, force-based skills. Sensorimotor skills are modeled using force-based discrete states, which describe qualitatively how contact is being made with the environment. The qualitative states can be identified from force signals by viewing them as projected clusters in the force sensor space. In this paper, we investigate the automatic clustering of force data by applying a competitive agglomeration algorithm to extract clusters which can be used for QCS classifier training. Experimental results are included using an automotive transmission assembly.

1 Introduction

Current manufacturing methods for robotic-controlled assembly rely on accurate positioning to ensure task completion, often through the use of special fixtures and precise calibration of the workspace. The reliance on precision positioning to achieve proper alignment creates problems in both programming and control of contact-based tasks. In current systems, assembly programming is typically accomplished by traditional text-based software development. The method requires the expertise of a specialized engineer and demands that the position points be captured accurately. During program execution, even small uncertainties in position may result in significant forces, hindering task completion and sometimes damaging workpieces.

As a means of addressing problems in both control and programming, we have been investigating the use of qualitative states for modeling and learning low-level force-based skills. Sensorimotor skills are modeled using force-based discrete states, which describe qualitatively how contact is being made with the environment. These qualitative contact states (QCS) are ultimately dependent on the geometric relationship (in position) between a grasped workpiece and its environment. However, to overcome uncertainties in position and orientation, we have been studying the force sensory patterns associated with the contact states, in an effort to identify the QCS directly from the signals on a wrist force sensor.

Qualitative states have been used previously to describe the topological contact between workpieces in assembly tasks. The contact formation was proposed by Desai and Volz [2] as a qualitative discrete state which describes how 2 or more objects make contact with each other. The original use targeted the automatic generation of assembly programs from CAD models. As such, most methods of identifying contact formations use detailed geometric models of the assembly parts, combined with position information and data from a wrist force sensor (e.g., [6]). One notable exception is the sensor-based method proposed by Hovland and McCarragher [8]. Another is the method proposed by Cervera et al [1], which also clusters force sensor signals to identify state information. Our work differs in the clustering mechanism and also includes a critical preprocessing step which minimizes sensor ambiguities.

In our previous work [12, 9], we introduced the concept of a single-ended contact formation (SECF), which provided a one-sided robot perspective of the contact formation. We showed how the SECF can be viewed as a projected cluster in force sensor space, and we presented two efficient classifiers which can be used to identify the SECF from force sensor signals alone.

In [13], we also demonstrated how a pre-trained SECF classifier can be used to facilitate skill acquisition by identifying a sequence of contact states from a demonstrated force profile.

In this paper, we refine the concept of a qualitative contact state and investigate the automatic clustering of force data to generate training sets for a QCS classifier. Using a force profile collected on an automotive tranmission assembly, a competitive agglomeration algorithm is applied to extract QCS clusters. An automotive transmission is chosen because it represents a complex, and thus, challenging assembly task.

In Section 2, we review the framework for the assembly skill model, and in Section 3 we describe the QCS characterization and clustering process. Experimental results and discussion are included in Section 4. Conclusions follow in Section 5.

2 Skill Model

The assembly skill is described as a sequence of QCS's and the transition trajectories that drive the system from one state to the next. (See also [13].) A directed graph is used for representation, where each node is a QCS and the connecting arcs represent the commands which generate the transition trajectories. In this case, the commands are reference velocity comands (relative commands), which direct the robot to move in a specified direction. That is, they are not based on absolute position. Linear segments are chosen between QCS nodes so that the final trajectory is piecewise linear. For robustness, more than one QCS sequence can be included in the graph, as long as each has the same goal state.

As shown in Figure 1, the control architecture used to drive the assembly has three parts which interact with the robot and robot controller: (1) a state classifier, (2) a supervisory controller, and (3) a force controller.

Because the assembly skill is driven by the QCS, the state classifier becomes a central part of the architecture. Each time the state changes, an event trigger notifies the state classifier and sends the current force sensor signals. Using the force data, the state classifier identifies the qualitative state class and sends this information to the supervisory controller.

The supervisory controller (SC) provides the high-level control in the skill model. After receiving a new QCS from the state classifier, the SC must generate the appropriate transition command which will drive the system to the next desired state.

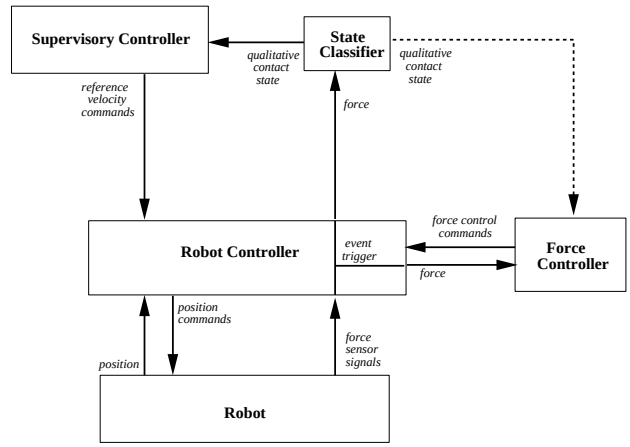

Figure 1: The Assembly Skill Model

The force controller (FC) provides the low-level control for the assembly skill, by generating force control commands to the robot. The default force control commands are implemented in the form of force limits. When the force (or moment) along any axis exceeds a threshold, a correction is made in the position command sent to the robot. The force controller can also receive state updates and thus, has the capability of changing the force control command depending on the QCS state.

3 QCS Clustering

The QCS describes the geometric relationship between a grasped object and the environment. To overcome uncertainties in position and orientation, force data from a wrist force sensor is used to identify the QCS, modeling the sensory patterns in the data. The force sensor returns data in 6 degrees of freedom (dof)– 3 dof for a force vector and 3 dof for a moment vector.

As shown in Figure 2, the force vectors (and similarly, moment vectors) of a QCS form cone-shaped patterns. The critical feature is the direction of the vector, not the magnitude [1]. To capture the direction, the data vectors are normalized, yielding a projection onto a unit sphere. Let f_x, f_y, and f_z be the force components of the sensor signal. Then, the normalized force components, f_{xn}, f_{yn}, and f_{zn}, are

$$f_{in} = \frac{f_i}{\sqrt{f_x^2 + f_y^2 + f_z^2}} \; for \; i = x, y, z$$

[1] Magnitude is used only to determine a contact condition from no contact.

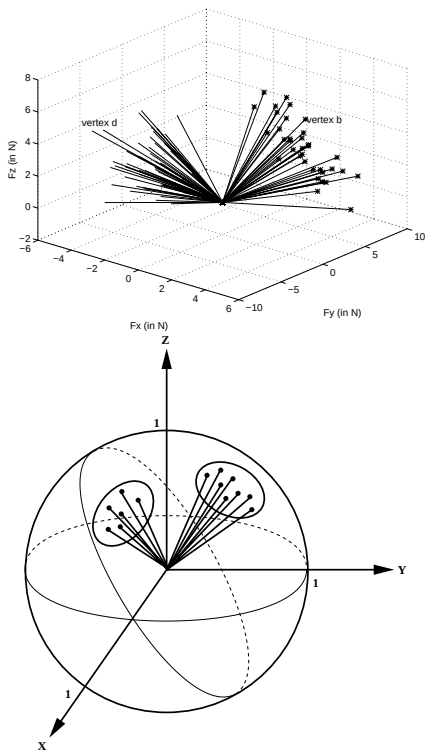

Figure 2: Force vectors for two qualitative contact states (top). Clusters formed by projecting the vectors onto a unit sphere (bottom).

Similarly, let m_x, m_y, and m_z be the moment components of the sensor signal. Then, the normalized moment components, m_{xn}, m_{yn}, and m_{zn}, are

$$m_{in} = \frac{m_i}{\sqrt{m_x^2 + m_y^2 + m_z^2}} \; for \; i = x, y, z$$

After the data vectors have been normalized, the resulting data sets look like clusters projected onto the unit sphere, as shown in Figure 2. The shape and size of the clusters depend on the motion constraints established by the contact (i.e., along which directions is motion allowed or not allowed). An edge QCS has an elongated elliptical shape whereas a vertex QCS has a circular shape. For a theoretical discussion, refer to [6, 7].

Although the QCS can be viewed as a static geometric relationship, the actual force and moment vectors will also depend on dynamic effects. For instance, if the grasped object slides along a face surface of the environment, a tangential force component will be created as a result of friction. This additional component has the effect of modifying the shape and/or size of the cluster. Vectors captured during the motion may even be outside of the original (static) cluster. Thus, we generalize the QCS and define it simply as a cluster in the force sensory space and are no longer restricted to mapping the geometric relationship into a single QCS. Indeed, a dynamic face contact may well appear as a new QCS cluster when compared to a static face contact. It is even possible that the two clusters may overlap, an issue that is addressed in [11].

Because of the noise and the variability in cluster shape, automatic clustering of QCS's is challenging. For the experiments presented here, a competitive agglomeration algorithm is used [3, 4]. This clustering algorithm has been chosen because it is relatively insensitive to prototype initialization or local minima and because the number of clusters is not required as input.

The algorithm combines the advantages of agglomerate and partitional clustering by using a two-part objective function. For a set of N vectors in 6-dimensional feature space, let $X = \{x_j | j = 1, ..., N\}$. For C clusters, let $\mathbf{B} = (\beta_1, ..., \beta_c)$ represent the cluster prototypes. The CA clustering algorithm minimizes the objective function, as shown below:

$$J_{CA} = \sum_{i=1}^{C} \sum_{j=1}^{N} (u_{ij})^2 d^2(x_j, \beta_i) - \alpha \sum_{i=1}^{C} [\sum_{j=1}^{N} u_{ij}]^2$$

where u_{ij} represents the degree of membership of vector x_j in cluster i, and is subject to

$$\sum_{i=1}^{C} u_{ij} = 1, \;\; for \; j \in \{1, ..., N\}$$

.

The first term utilizes the distance from vector x_j to the prototype β_i, as shown by the term $d^2(x_j, \beta_i)$. In our case, the distance measure is for ellipsoidal clusters as proposed by Gustafson and Kessel [5]. This first term controls the shape and size of clusters and reaches a global minimum when $C = N$. The second term is used to control the number of clusters and reaches a global minimum when all points are combined into one cluster ($C = 1$). By combining both components and choosing an appropriate α, the CA algorithm attempts to find a balance between the two terms by partitioning the data set into the smallest possible number of compact clusters.

4 Experiments

The experiments described here investigate the feasibility of automatically extracting QCS clusters from

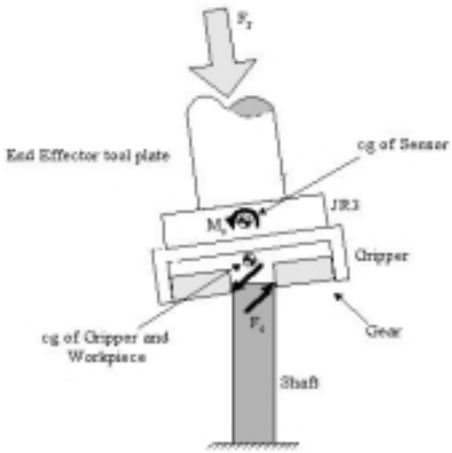

Figure 3: Assembly Operation

a force profile of an assembly operation. A transmission assembly was chosen because it represents a complex assembly where one gear mechanism must correctly mesh with several other gears. As such, it would be difficult to collect data for a known QCS as was done previously [9].

4.1 Experimental Setup

For the experiments, a Puma/Unimate 762 robot was programmed to drive a gear onto a shaft using a sliding fit, as shown in Figure 3. This is essentially the opposite of the peg-in-hole; instead, the hole is inserted over the peg. Binding forces and moments were measured with a JR3 force sensor. To prevent damage to the equipment during the tests, a pneumatic breakaway joint was used to couple the shaft to the bench. The pneumatic pressure was empirically established to form a rigid test piece. The end-effector gripper mock-up was designed to model the mass and geometry of standard off-the-shelf grippers.

Three test sequences were designed. The first was motion of the gear onto the shaft (*position 1* to *position 2*). The second test sequence was the gear motion down the shaft (*position 2* to *position 3*). The final design sequence was motion from *position 1* to *position 3*. In addition three offset conditions were established. The first offset condition established the baseline (*Zero-Offset*). The second offset condition was designed for an offset in a single axis normal to the gear motion (*Y-Offset*). The final offset condition was designed with a coupled offset in the X-axis and Y-axis (*XY-Offset*). The offset conditions are shown

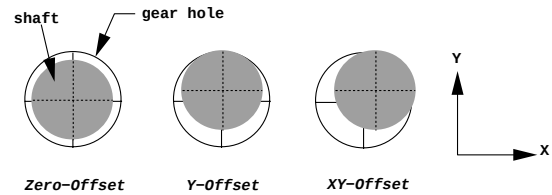

Figure 4: Offset Conditions

in Figure 4; the Y-offset was 1.0 mm and the X-offset was 0.75 mm. Twenty tests were conducted for each motion sequence and offset combination, using position control only. Although the same starting position was used for each test in a series, the actual position varied according to uncertainties present in the robot and controller [2].

4.2 Clustering Results

Results are included here for the test sequence of *position 2* to *position 3*. We compare a representative run from each of the offset conditions. Complete results can be found in [10].

The force and moment profiles for the three runs are shown in Figures 5, 6, and 7. An arbitrary index number is assigned to each cluster, and these clustering results are included with the corresponding force profile to show the time series results.

The CA clustering algorithm uses 6-dimensional input vectors; for visualization we show projected 2-dimensional plots for each run, in Figures 8, 9, and 10. The cluster sequence is shown with each graph; in each case, the goal state is represented by $\circ$.

4.3 Discussion

Although the plots in Figures 8, 9, and 10 provide 2-dimensional projections only, consistencies in the data are evident, both in the shape and in the goal state. Comparing corresponding input dimensions, the center of the goal state is approximately the same for each run. This is critical for being able to recognize the goal condition, and therefore being able to stop the operation as appropriate.

Also, we can observe a greater dispersion in the data sets, for the test runs with offsets. This is of course expected because the offset conditions produce a greater range in the QCS sensor space.

Finally, there is an observable QCS sequence in the assembly operation, which follows our model of the as-

[2] The manufacturer's documentation states position repeatability at +/- 0.2 mm.

sembly skill. The initial assessment of the clustering results is promising; however, this is just a first step towards investigating the feasibility of the approach. We are currently investigating appropriate cluster validity measures, to further assess the performance of the clustering algorithm. We also intend to cluster multiple test runs together. Finally, we plan to use the extracted clusters as training data for a QCS classifier. The ultimate test will be to use the trained QCS classifier to control an actual assembly task.

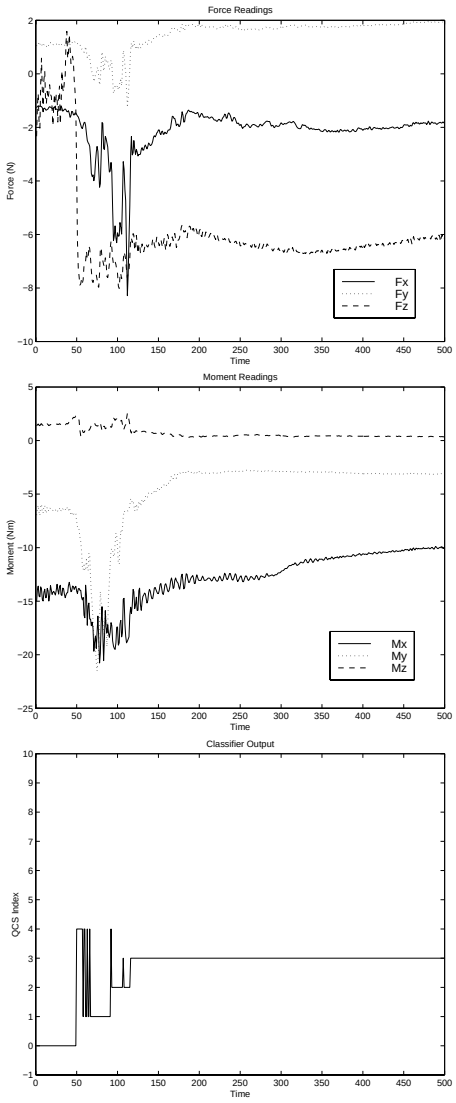

Figure 5: Time Series Clustering Results: Zero-Offset

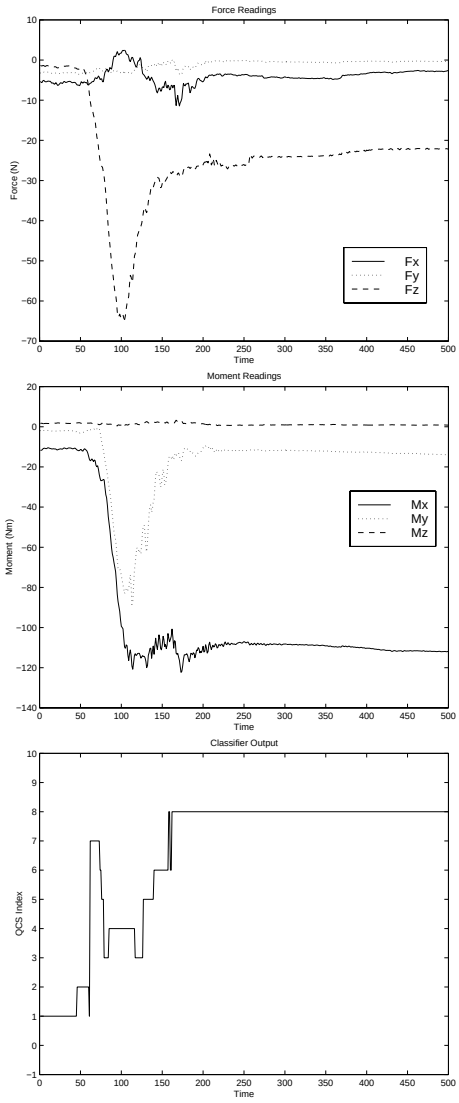

Figure 6: Time Series Clustering Results: Y-Offset

5 Conclusion

In this paper, we have presented a characterization of the qualitative contact state and described experiments in automatic clustering of force data. Using a force profile collected on an automotive transmission assembly, a competitive agglomeration algorithm is applied to extract clusters, thus generating training sets for a QCS classifier. Results of the clustering experiment are included.

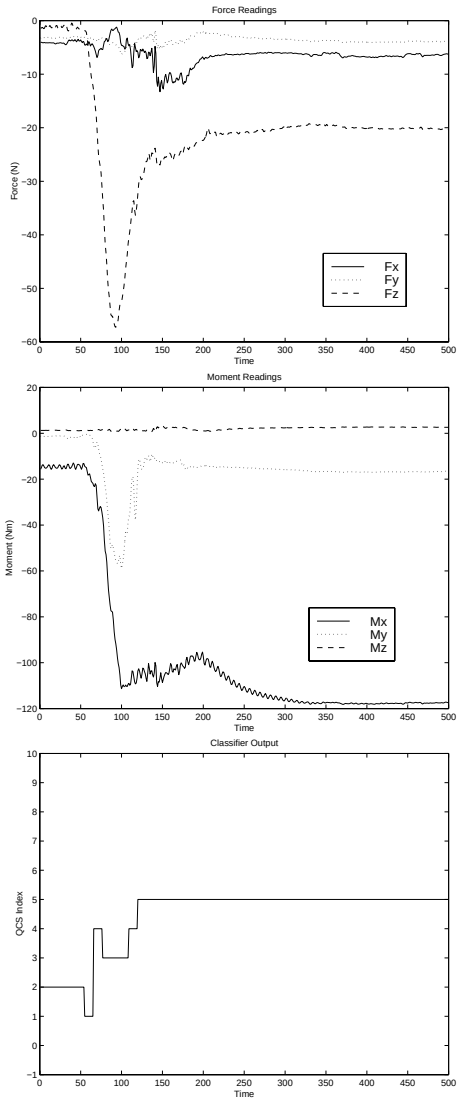

Figure 7: Time Series Clustering Results: XY-Offset

The work described here proposes a new way of processing force sensor signals that we hope will facilitate the sensor-based identification of qualitative contact states. Ultimately, we would like to make assembly tasks easier to control and easier to program, thus providing a range of new opportunities for robotic tools.

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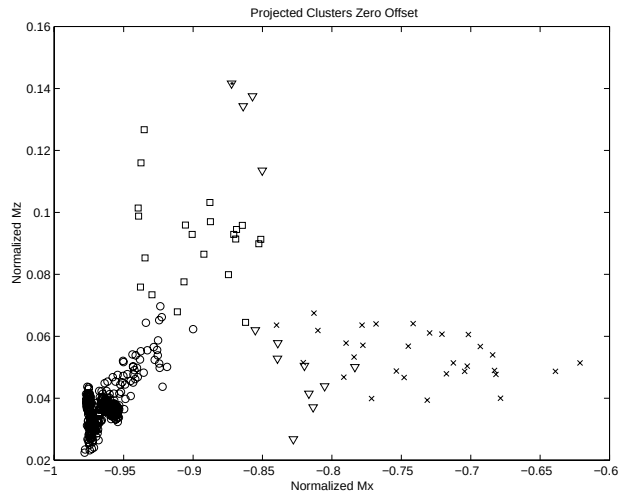

Figure 8: The Zero-Offset run produced 4 clusters. The sequence is $\bigtriangledown \times \square \circ$.

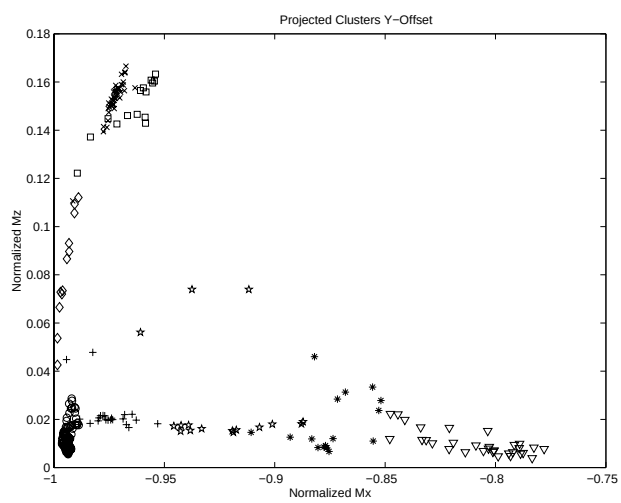

Figure 9: The Y-Offset run produced 8 clusters. The sequence is $\times \square \diamond * \bigtriangledown * \star + \circ$.

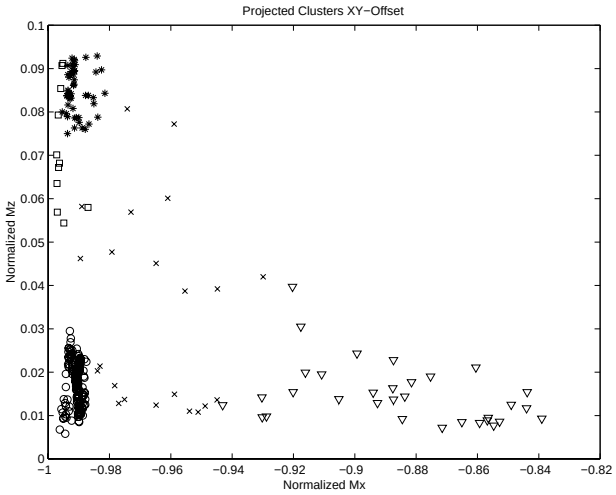

Figure 10: The XY-Offset run produced 5 clusters. The sequence is $*\square \times \bigtriangledown \times \circ$.

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