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Generalized Recognition of Single-Ended Contact Formations for Use in Automated Assembly Operations

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**AMARILLO NATIONAL RESOURCE CENTER FOR PLUTONIUM/
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Final Thesis Report on

**Generalized Recognition of Single Ended Contact Formations
for Use in Automated Assembly Operations**

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Abstract

Robots are preferred over any other form of automated machines for assembly tasks due to their capability of being programmed to perform a variety of tasks. However, in the present day industries, the turn around time for new designs have dramatically reduced. Therefore, the need for robots which can adapt its teaching and programming to new situations is strongly felt. This is especially true in the tasks such as assembly operations, which involve the robot making frequent contacts with its environment.

This research addresses the problems that arise due to small changes in the work settings after the system has been programmed or trained. In an industry setting it is very likely that changes such as orientation and translation of the grasped object with respect to the robot axes can occur due to many unforeseen causes. The research here is focused on generalizing a Hybrid

Control System, in which an assembly skill is described as a sequence of qualitative states and the desired transition between the states. In this case, the qualitative state takes the form of a single-ended contact formation, which describes how a grasped object touches its environment. Skill acquisition involves learning the sequence of qualitative states, the transition between those states, and the mapping from the sensor signals to the qualitative states.

We discuss impact of changes in the orientation and the position of the grasped object with respect to the robot axes on the recognition of these qualitative states. We also propose a method of decreasing the performance degradation caused by this orientation change in recognition of these qualitative states, by adapting to the new situation with as minimum retraining as possible. Experimental results are presented which illustrate and validate the approach.

DEDICATION

This thesis is dedicated to my family.
To my father, for his encouragement. To my

loving mother, for her support. To my
brother, for guiding me in the right direction.
To my friends, for bringing joy to my life.

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1. INTRODUCTION

1.1 Motivation

Many repetitive tasks in the industrial settings have successfully incorporated robots for performing autonomous operations. One of the many applications of industrial robots is assembly operation. Assembly operations involve the manipulation of moveable objects, which make contact with the work environment. Robots are distinguished from other automated machines by their capability of being reprogrammed to perform a variety of tasks. In some cases, the robots may even perform the task better than the human operators may. However, this functionality is very much dependent on maintaining a structured and controlled environment. Even in a structured manufacturing setting, robot programming can be time consuming, may require special expertise and is heavily dependent on the nature of the task. The level of autonomy and learning in robots still has challenging problems.

Robot programming involves an iterative procedure of determining the motion strategy for a particular task and calculating the precise position information using the geometric data of the grasped objects and the environment.

Depending on the nature of work, the robot may be asked to perform repetitive or non-repetitive tasks. The non-repetitive tasks are generally exception cases, which are not a part of the regular operations. These may occur due to malfunctions or failure to follow the intended procedures. If it is a new task not performed previously, the robot may need some other instructions or a total reprogramming. A human operator uses his intelligence to adapt his previous training to the new situation. The robot will be more functionally useful if it has some level of local autonomy in deciding a new strategy.

As more sophistication is added, the robot may eventually serve as an assistant to a human operator. The robot may be used to perform the more menial or more dangerous tasks as the human worker and robot work side-by-side (functionally if not physically). The human-robot relationship might be compared to that of a seasoned foreman working with an inexperienced human assistant. In such a situation, the robot may require on the job training just as the human worker might.

In present day industries the turn around time for new designs has decreased by a great amount. So the need for robots which can adapt their training to new situations is more in demand as reprogramming is a lengthy and a costly affair. There are many research minds put to the task of making robots intelligent tools, which in turn make the job easier for the human worker or allow a human to avoid a hazardous environment.

This research addresses the problems involved in assembly tasks. When people perform assembly tasks, they use vision until the grasped object contacts the environment. From that point, the haptic sense (feel of forces due to touch) dominates. In other words, the instructions to a human operator are in terms of the contact formation. For example, the human operator might be instructed as follows: touch the surface A with surface B and slide along surface B in direction C until edge E comes in contact with a surface. A human operator is able to determine the nature of the contact formation from the forces he feels.

This investigation looks at advantages of implementing touch sensing on automated machines. The advantages of having touch sensing can be enjoyed in one way if the system is able to detect if the force signal was caused due to an edge touching a surface, surface touching a surface or a point touching a surface. This way the system can be programmed to achieve a type of contact

rather than moving to a particular position and orientation. This is analogous to the way the human acts and it is naturally extensible to different types of parts.

In summary, the motivation behind this research is to make the process of recognizing the contact formation more adaptive to new situations, which they might encounter. This research also looks at using previous experience and making the reprogramming simple.

1.2 Research Goals

The research discussed in this thesis will focus on the problem of making the recognition of the type of contact more adaptable to new situations. The research looks at the various ways attempted in the past which address the problem of recognizing the contact formations and chooses the one which is considered most suitable to use in assembly tasks in a routine industrial setting.

In real life situations it is quite safe to assume that there can be some variations in the way an object is picked up by a human. A human recognizes the object and its different areas by the use of vision and touch. A robot tries to overcome its limited or lack of these capabilities by use of specially designed fixtures and geometric data of the object with respect to such a fixture provided by the programmer to identify the object.

Most methods of contact type recognition depend on the relative position and orientation of the object with respect to the fixture (which might be a robot's manipulator arm) in which it is held. The research goals are as follows:

- To study the effect of an arbitrary orientation and position change of the grasped object on the task of contact recognition.
- To study the effect of orientation and position change on the performance of a

selected method of contact type recognition.

- To develop an algorithm to reverse the effects of orientation changes and adapt the original process of recognition to new situation.
- To be able to accomplish adapting to the new situation using minimal collection of new data about the object or its interactions with the environment.

The study is carried out on a static force based contact recognition system developed by M. A. Skubic (1997). We will explore the possibilities and limitations in trying to adapt training data to new situations.

1.3 Outline

The reminder of this thesis is organized as follows. The background research will be discussed in Chapter 2. Chapter 3 will present the description of the effect of orientation change on the force and moment data, its effect on the classifiers and give a detailed description of the algorithm and the mathematics involved in reversing the effect of orientation change on the classifiers. In Chapter 4, the hardware and software of the test bed will be described. The experimental results along with analysis will be reported in Chapter 5. We will conclude with Chapter 6, citing the accomplishments, as well as limitations and suggestions for future work.

2. RELATED RESEARCH

This section gives an overview of related research and background in the general area of contact recognition. The intent is to show the evolution of research, which resulted from both limitations and improvements in technology.

In the past, various methods were tested in the area of contact type recognition between two or more objects. Most of these methods can be broadly classified into three main groups: position or geometry based methods, force based methods and hybrid methods that use both force and position data in contact type recognition. These topics will not be discussed in detail in this chapter; however, related references will be introduced through the course of this thesis. This chapter gives a brief description of each of these three methods as well as discusses their limitations for use in assembly operations.

2.1 Position/Geometry Based Methods

Most methods of identifying contact formations use detailed geometric models of all the parts involved in the contact to determine the contact formation type. These methods generally solve analytical equations to obtain the contact formation.

Hirai and Asada (1990) derived the contact classifiers from the geometric model using polyhedral cones. The ranges of possible forces and displacements, which can be measured at each contact formation, were represented as union of polyhedral convex cones (PCC). The face vectors of the PCC's were used to determine the contact formation from the force signals.

Desai and Volz (1989) identified the contact formation by first formulating a hypothesis and then verifying that it was consistent with the sensed force signals. They used static equilibrium equations and solved for the contact forces and moments. In cases where the contact forces could not be determined, or ambiguity existed, active force

sensing was used. Motions were made along the separation cone (a separation cone is a set of all motions that result in a break of contact) and more sensing data was collected.

McCarragher and Asada (1991) used an analysis of rigid body dynamics to identify the contact formation between objects. Constraints were added to the equations of the motion with LaGrange multipliers and a velocity constraint matrix. For each discrete contact formation, all possible quality states were enumerated, where a quality state is defined as a unique combination of positive, negative, or zero values for each position, velocity and acceleration term in the equation. Qualitative templates were then pre-calculated as the sequence of quality states that represent the type of motion expected to achieve the desired contact state.

The position-based approaches require detailed information about the position of all the objects involved in a contact formation and they also require a complete geometric description of the objects. In an industrial setting this information is prone to errors and uncertainty. It becomes more difficult for these methods to include the effects of friction, sensor noise and non-linear behaviors.

2.2 Force Based Approaches

Force based approaches are used as an alternative to using geometric information and overcome the limitations of using geometric data. The force-based methods can further be classified into two categories static force based approaches and dynamic force based approaches.

The dynamic force based approaches try to recognize the contact type by continuously modifying the applied force both in direction and magnitude. These methods try to capture the dynamic effects caused by transition from one contact state to another.

Hovland and McCarragher (1996) used fast fourier transforms to capture the dynamic

nature of the contact change and hidden Markov Models to model the information. To implement this method in real time involves high computational costs and this is its main limitation.

The static force based approaches use prior training to recognize the contact state from a force signal, moment signal or a combination of both. These methods do not require multiple force/moment signals to recognize a contact state. Hara and Yokogawa (1992) used fuzzy sets to model contact formation. However, only a small number of contact states for one case were considered. No attempt was made to provide a generalized methodology for applying the approach to other workpieces or contact tasks.

M. A. Skubic (1997) addressed the above problems and formulated a more general contact recognition scheme that can be extended to different parts. Both fuzzy logic classifiers and neural networks were used to recognize the contact states. This method provides a better way of dealing with

the uncertainties involved due to friction and non-linear sensors. But this method could not deal with orientation and the position changes of the object with respect to the force/moment sensor after the training.

2.3 Hybrid Approaches

In the position/geometric-based approaches, the complexity of the equations involved becomes very high as the number of objects in the scene increases and as the geometric description of the object gets more intricate. Some approaches were used to lessen the complexity involved by supplementing the geometric information with force signal data.

Farat, Graves and Trinkle (1995) used linear programming to determine the feasibility of a contact formation, based on the force signals and the geometric model. Good results were achieved through this method, but the performance rapidly decreases as the uncertainty of the parameters of the geometric model increase.

3. METHODOLOGY

In this chapter, the main ideas are presented for adapting the previous training data to a new situation. Ideas will be drawn from previous work, but in many cases, we will look at the problem (and solutions) from a new perspective. Suggestions will be made in uniting and extending the concepts in new ways. In doing so it is important to keep the focus on the overall purpose and goals of the research, which is to make the automation of robots more adaptable to new situations.

The 'new situation' here is the orientation and position change of the grasped object with respect to the sensor axes. The following two sections describe what is meant by a 'contact formation' and 'an orientation and position change.' The next two sections discuss the effect of the change on the force and moment signals, which are used to classify the single ended contact formations (SECFs), and discuss the means of calculating the amount of translation and rotation with respect to the sensor axes involved in the change to the new situation. The calculations use the force and moment data obtained from the force/torque sensor. This data is collected for different contact formations both before and after an orientation/position change occurs. The final section describe a comprehensive algorithm which initially determines the translation and rotation components from the force and moment data and then describes a series of steps required to transform the classifier data to match the

original data using the translation and rotation information.

The overall objective is to make changes transparent to the system recognizing the SECFs. Two methods are used. In the first, the information about the forces and moments in the classifier data files is transformed approximately before the classification of the operational data. The second method of adapting is applying an inverse transformation on the incoming force and moment data so that the original classifier can be used with out any modification. The fuzzy logic classifier developed implemented by M. A. Skubic (1997) was tested in the first method and the neural network classifier was used for the second method.

3.1 Contact Formations

To meet the stated goal, we will first look at the definition of contact formation. Contact formations are a set of configurations with identical, elemental contacts between pairs of topological elements (Desai and Volz, 1989). The contact formation (Desai and Volz, 1989) provides a qualitative description of how two or more objects make contact with each other, reflecting the geometric relationship (e.g., edge 1 of the grasped object touches side B of the environment).

Figure 1 shows an example of three different types of contact formations. As such, the possible contact formations depend on the relative size and shape of the objects, reflecting the geometric relationship.

Figure 1: An Example Showing Three Types of Contact Formations

Figure 2: An Example of Two Contact Formations which belong to the Same Class of Single-Ended Contact Formations

In contrast, a single-ended contact formation (SECF) (Skubic, 1997) provides a one-sided description of how a grasped object touches its environment (e.g., edge 1 of the grasped object touches any side in the environment). It does not attempt to distinguish between similar contact points in the environment. Figure 2 shows an example of two contact formations in which an edge of the moveable object is touching different sides of the fixed object in the environment. Because both the contact formations involve the same edge of the moveable object, they provide examples of the same SECF.

3.2 Orientation and Translation Change

In this thesis we look at a static forced based method used by M. A. Skubic (1997) to

identify the SECFs. What this means is, we have a robot with a force/torque sensor mounted on its end effector. The grasped object is held between the sensor and the environment. Force and torque signals are measured relative to the robot's end effector coordinate system. The objective is to achieve a SECF between the object and the environment, measure the force/torque, and identify the SECF using a classifier. To accomplish this, the classifier needs to be trained. To train the classifier, the object is grasped once and placed multiple times into known SECFs. During each SECF, force/torque readings are recorded. This data provides a "signature" of the SECFs, which the classifier uses to train itself to recognize the SECF.

Figure 3: Force Vectors of an Edge of a Square Block Workpiece

Figure 4: Moment Vectors of an Edge of a Square Block Workpiece

Figures 3 and 4 show the sample force and moment vectors collected for a single training SECF. In each case, the vectors shown represent the raw data from the force sensor, as measured in the sensor frame.

As shown in the figures, the force and torque vectors in each data set form a 'cone-shaped' pattern. The spread of these force and moment vectors is dependent on the geometric shape of the object and reflects the motion constraints existing between the grasped object and its environment. Other factors affecting the shape of the pattern include friction, uncertainty due to sensor noise, and errors that may occur in the data collection process. The classifiers used to identify the SECFs in the method followed by M. A. Skubic (1997) consisted of a fuzzy logic and a neural network method. Both of

these classifiers are dependent on the orientation and position of the grasped object relative to the force/ moment sensor.

In practice, the object may be re-grasped after the training, resulting in a change in the relative position and orientation between the force moment sensor and the grasped object. The direction of the force applied to a particular point on the grasped object changes during an orientation change. For example, consider a case where a face makes contact with another face. The contact force between the faces (assuming that there is no friction) is normal to that face. Therefore, if the object is grasped with an orientation different than that during training, some of the faces and hence the forces have changed.

Figure 5: Orientation Change of Square Block Workpiece

Figure 6: The Projection of a Set of Vectors onto a Unit Sphere

Also since the moment about an axis depends on the distance between the point of application of the force and the axis, some moments are affected if the grasped object is translated relative to the training grasp. Figure 5 illustrates an orientation and position

change from the training grasp of the object with respect to the sensor axes.

The fuzzy logic classifiers used by M. A. Skubic (1997) are dependent on the direction of the means and standard deviations of the force and moment training

signals collected from each single ended contact formation. The direction of the mean is obtained by normalizing the sample force vectors and averaging them. Figure 6 shows the projection of these force signals onto a unit sphere. The fuzzy logic classifier tries to capture the size, orientation and the spread of the force and moment signals for each SECF.

The fuzzy logic classifier used by M. A. Skubic (1997) calculates the membership of each of six components namely force and moment in X, Y and Z directions of the sensor frame. The membership functions are generated automatically using supervised learning. Training data as shown in Figures 5 and 6 were acquired by demonstrating each SECF class and collecting the force and moment signals generated. For each contact class feature j ("features" here refer to the components of force and moment in X, Y and Z directions of the sensor axes), the mean, μ_j , and standard deviation, σ_j , are calculated. These are used as parameters to generate the membership functions, $\pi_j(r)$, as shown below; here 'r' refers to a single set of force and moment signal.

$$\pi_j(r) = 1 - e^{-\left(\frac{3\sigma_j}{|\mu_j - r|}\right)^3}$$

for $j = F_x, F_y, F_z, M_x, M_y, M_z$

The fuzzy conjunction operator used to combine the membership functions is the

Hamacher product (Zimmerman, 1991). 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 the features are combined. As an alternative, the Hamacher product can be reduced to the following form:

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

Then the combined product is compared with an experimentally obtained threshold to determine its class (Table 1 shows the membership parameters for a sample SECF class).

In practice, the object maybe re-grasped after the training, resulting in a change in the relative position and orientation between the force moment sensor and the grasped object. Figures 7 and 8 illustrate the shift in the cone orientation caused by such an orientation change in terms of actual force and moment vectors.

Figure 7: Change in the Direction of the 'Cone' of Force Vectors Caused by an Orientation and Position Change

Figure 8: Change in the Direction of the 'Cone' of Moment Vectors Caused by an Orientation and Position Change

Table 1: Membership Function Parameters for a Sample SECF Class

Parameter	F_x	F_y	F_z	M_x	M_y	M_z	Zero
μ	-0.640	-0.219	0.644	0.121	-0.936	-0.021	-0.000N
σ	0.214	0.155	0.239	0.318	0.073	0.048	0.979N

Table 2: Sample Input Vectors (Forces in N; Moments in N-mm)

Vector	F_x	F_y	F_z	M_x	M_y	M_z	$ f $
Input vector	-3.96	0.68	6.01	-315.56	-624.57	-75.50	7.23
Normalized vector	-0.55	0.09	0.83	-0.45	-0.89	-0.11	1.00
Membership grade	1.00	0.96	1.00	0.99	1.00	0.99	N.A

It can be seen from the membership function that the classifier tries to find the degree by which a force vector or a moment vectors lies in the 'cone' identified during the training process. Table 2 lists a sample force and moment vector and the membership grade of their individual features can be interpreted as the possibility of the 'X' component of the force ' F_x ' lies in the 'cone' is 100% and that of 'Y' and 'Z' components are 96% and 100% respectively. Similarly the 'X','Y' and 'Z' components of the moment have possibilities of 99%, 100% and 99% respectively of lying in the 'cone.'

3.3 Effect of Orientation and Position Change on Force Signals

The orientation and position change of the grasped object with respect to the sensor axes effects both the orientation and the spread of the force and moment signals. This is illustrated in the sample data shown in Figures 7 and 8. When a force is applied to a plane it acts in a direction perpendicular to that plane assuming there is no presence of friction. In the event of rotation of the plane by angle ' θ ' about an axis K represented by

(K_x, K_y, K_z), the perpendicular to that plane also rotates by the angle ' θ ' about an axis K. Hence the direction of the force rotates in the same manner.

This shows that using the information from one force vector, the change in other force vectors could be calculated. If the object rotates about the line of action of the force, there is no change in the direction of the force. But the forces perpendicular to the axis of rotation show the maximum change. So just by examining one force we may not be able to determine the orientation change.

The rotation caused by an orientation change of the grasped object can be represented as a 3x3 matrix, which represents a transformation of the forces with respect to the sensor frame. Say R is this Rotation matrix, and is represented as shown below:

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}$$

where r_{ij} , $i,j=1..3$ represent 9 real numbers.

If F_1 is the direction of force before an orientation change and P_1 is a force after an orientation change, then P_1 can be written in terms of F_1 as follows:

$$P_1 = [R] \otimes F_1$$

where $F_1 = (F_{1x}, F_{1y}, F_{1z})^T$ and $P_1 = (P_{1x}, P_{1y}, P_{1z})^T$

where ' $\otimes$ ' represents matrix multiplication.

This can also be written as three linear equations as follows:

$$\begin{aligned} P_{1x} &= r_{11} \cdot F_{1x} + r_{12} \cdot F_{1y} + r_{13} \cdot F_{1z} \\ P_{1y} &= r_{21} \cdot F_{1x} + r_{22} \cdot F_{1y} + r_{23} \cdot F_{1z} \\ P_{1z} &= r_{31} \cdot F_{1x} + r_{32} \cdot F_{1y} + r_{33} \cdot F_{1z} \end{aligned}$$

In these equation there are nine unknowns. To precisely calculate the ' R ' matrix using this type of linear equations we need more equations. We can get more constraints by using the orthonormal property of the Rotation matrix, which can be expressed as

$$R \otimes R^T = I$$

where ' I ' is a 3 by 3 identity matrix, which results in the following equations:

$$\begin{aligned} r_{11}^2 + r_{12}^2 + r_{13}^2 &= 1 \\ r_{21}^2 + r_{22}^2 + r_{23}^2 &= 1 \\ r_{31}^2 + r_{32}^2 + r_{33}^2 &= 1 \\ r_{11} \cdot r_{21} + r_{12} \cdot r_{22} + r_{13} \cdot r_{23} &= 0 \\ r_{11} \cdot r_{31} + r_{12} \cdot r_{32} + r_{13} \cdot r_{33} &= 0 \\ r_{31} \cdot r_{21} + r_{32} \cdot r_{22} + r_{33} \cdot r_{23} &= 0 \end{aligned}$$

Now we have enough equations to be able to solve for the matrix ' R '. But this method results in a trivial solution if the rotation of the object occurred around the line of action of the force. So we need any second F_2 which is not parallel to the first force to deal with the above problem. Using the orthonormal property in the above stated manner will

require us to solve quadratic equations. We can avoid this if we can get information about one more vector before and after the rotation thereby resulting in nine linear equations.

Let the third vector be a vector perpendicular to first two vectors. A vector perpendicular to two vectors is obtained by taking their cross product, which implies that $F_n = F_1 \times F_2$. As an inherent property of a rotation matrix it preserves the orientation between the transformed vectors. So the transformed third vector P_n can be obtained by cross product of P_1 and P_2 .

So if F_1 and F_2 are mean unit vectors of any two SECFs of a rigid body, and P_1 and P_2 are mean unit vectors of the same two SECFs after an orientation and a position change, the rotation involved in that orientation change can be calculated by solving the following simultaneous linear equations:

$$\begin{aligned} P_1 &= [R] \otimes F_1 \\ P_2 &= [R] \otimes F_2 \\ P_n &= [R] \otimes F_n \end{aligned}$$

where P_n is the unit vector of cross product of P_1 and P_2 ($P_1 \times P_2$), and F_n is the unit vector of cross product of F_1 and F_2 ($F_1 \times F_2$),

where ' $\times$ ' represents cross product.

Hence to calculate the rotation involved in the orientation change it is required to recollect data from two faces in the new orientation. The other force vectors can be calculated by pre-multiplying them with the rotation matrix obtained from the above procedure.

In a rigid body, the relative orientation between different faces is always fixed. This is a direct deduction from the definition of a rigid body. When a body translates in X, Y and Z directions, the orientation of the planes do not change. This means there is no change in the direction of the normals to the planes.

So the translation has no effect on the direction of the forces.

3.4 Effect of Orientation and Position Change on Moment Signals

Moment can be mathematically represented as the cross product of a position vector to the point of application of force and the force itself. The orientation and the position change can be expressed as a rotation about an arbitrary axis passing through the sensor origin and a new translation. If there is a translation in any direction other than along the line of action of force during the position change, then the moment arm vector changes thereby causing a change in the moment. We have seen earlier that any orientation change results in the change in force direction.

Therefore, both rotation and translation affect the moments.

First, let us consider the effect of rotation on the moments. Figure 9 illustrates a case wherein the force rotates about the point of its application without translating.

Figure 9: Effect of Rotation on the Moment Vector

In Figure 9 let F_1 represent the original force in XZ plane before an orientation change and let M_1 be the moment caused due to F_1 . Let F_2 represent the force after an orientation change and let M_2 be the new moment caused by this force.

We know that any force can be written as sum of two or more forces. So we can represent the new force F_2 as the sum of three forces one in the direction of the position vector R_1 , one in the direction of the original force F_1 and one in the direction perpendicular to the plane formed by the force vector and the position vector which is parallel to the moment vector.

$$F_2 = C_1 * f_1 + C_2 * r_1 + C_3 * m_1 \quad (1)$$

where the '*' operator represents the scalar multiplication with a vector.

In the above equation f_1 is a unit vector along F_1 and r_1 is a unit vector along the original position vector. This is represented in Figure 9 by a line joining the point of action of the force with the sensor origin R_1 and m_1 is the unit vector along M_1 ; C_1 , C_2 and C_3 are real numbers which represent the components of the new force F_2 in the three directions and can be calculated as follows:

$$C_1 = F_2 \cdot f_1 \quad (2)$$

$$C_2 = F_2 \cdot r_1 \quad (3)$$

$$C_3 = F_2 \cdot m_1 \quad (4)$$

where ('•' represents the dot product operator).

The Moment ' M_2 ' due to force F_2 is given by the expression $M_2 = R_2 \times F_2$ where R_2 is the vector joining the sensor origin and the point of action of the force F_2 . Here $R_2 = R_1$ as we assumed that there is no change in the position. So M_2 can be expressed as:

$$M_2 = R_1 \times F_2 \quad (5)$$

Then the moment due to F_2 is the sum of the moments due to force along R_1 ($C_2 * r_1$), F_1 ($C_1 * f_1$) and along M_1 ($C_3 * m_1$). Substituting these in Equation 5, M_2 can be written as follows:

$$M_2 = R_1 \times (C_2 * r_1 + C_1 * f_1 + C_3 * m_1).$$

Since vector cross product is distributive, we can rewrite the above equation as follows:

$$M_2 = R_1 \times (C_2 * r_1) + R_1 \times (C_1 * f_1) + R_1 \times (C_3 * m_1)$$

$$M_2 = C_2 * (R_1 \times r_1) + C_1 * (R_1 \times f_1) + C_3 * (R_1 \times m_1)$$

$R_1 \times r_1 = 0$ since R_1 and r_1 are in the same direction.

Therefore:

$$M_2 = C_1 * (R_1 \times f_1) + C_3 * (R_1 \times m_1) \quad (6)$$

We know that:

$$M_1 = R_1 \times F_1 \quad M_1 = R_1 \times (K * f_1)$$

where K represents the magnitude of the force:

$$M_1 = K * (R_1 \times f_1)$$

Rewriting the above equation we get,

$$R_1 \times f_1 = M_1 / K \quad (7)$$

Substituting Equation 7 in Equation 6 we get,

$$M_2 = C_1 * M_1 / K + C_3 * (R_1 \times m_1).$$

Therefore, we can write:

$$M_2 = (C_1 / K) * M_1 \text{ when } C_3 = 0.$$

C_3 is equal to zero if the force rotates about M_1 , thereby having no component in that direction. So we conclude that if the

force rotates in a plane formed by the force and the moment arm the moment does not change direction but there is a change in magnitude.

Now, let us consider a case where the new force is parallel to M_1 , then there is no component along force F_1 as M_1 is perpendicular to F_1 , which implies $C_1 = 0$. Substituting $C_1 = 0$ in Equation 6 we get:

$$M_2 = C_3 * (R_1 \times m_1).$$

We can see from the above equation that there is a direction change in the new moment and M_2 is perpendicular to m_1 as the force is rotated by 90 degrees about the moment arm. Since the moment is the cross product of position vector and force when the force vector rotates about the moment arm, the moment also rotates by the same amount and about the original moment arm.

Therefore, we conclude that in the case of the arbitrary rotation of force about the point of application of force, the moment arm rotates about the original moment arm by the same amount as the force rotates from the plane formed by the original force and position vector, and the magnitude is affected by the rotation component in the plane formed by the original force and moment arm.

3.5 Algorithm to Obtain the Relative Rotation and Translation Components by Analysis of New Data

This section presents an algorithm for finding the rotation and translation components by the analysis of new data collected in the new situation. The new situation is assumed to be a result of an orientation and position change relative to the force/torque sensor, caused by the change in the grip of the object. This section also addresses the type of data required for successful calculation of these parameters.

The algorithm uses the force and moment data resulting from contact

formations of two perpendicular faces, 'A' and 'B,' of the object with the work environment both before and after an orientation/position change. The force and moment signals are collected such that the sample data is a good representation of the various situations that can arise in an actual assembly operation. These situations include the effect of factors such as friction, uncertainty due to sensor noise, and other errors that may occur in the data collection process such as partial contact formations. The force/moment data is collected over an interval time. Then a representative force and moment is obtained by taking an average. For example the experiments conducted to verify the methods proposed here used an average of '1500' force and moment signal data points for each face and edge.

The subscript 'i' in variables can take the value of 1 or 2. The subscript 1 refers to the value of that quantity in the original position and orientation and the subscript 2 refers to the values in the new situation. Following are the variables, which will be used in this algorithm.

F_{a_i} is the mean force data for face 'A' SECF.

f_{a_i} is a unit vector along F_{a_i} ,

F_{b_i} is the mean force data for face 'B' SECF.

f_{b_i} is a unit vector along F_{b_i} ,

M_{a_i} is the mean moment data for face 'A' SECF,

m_{a_i} unit vector along M_{a_i} ,

M_{b_i} is the mean moment data for face 'B' SECF,

m_{b_i} unit vector along M_{b_i} ,

R_{a_i} is the mean position of application of force F_{a_i} ,

R_{b_i} is the mean position of application of force F_{b_i} ,

M_c is the new Moment considering only an orientation change in the moment.

Step 1: $C_1 = \frac{|F_{a2}|}{|F_{a1}|}$

Step 2: $C_2 = Fa_2 \bullet ma_1$

Step 3: Calculate the moment M_c considering only the rotation aspect as discussed in the earlier sections.

$$M_c = C_1 * Ma_1 + C_2 * (Ra_1 \times ma_1)$$

Step 4: $\Delta m = Ma_2 - M_c$

Step 5: In the earlier sections we have seen that Δm is solely due to translation as rotation has already been considered. Let ' ΔT ' be the position change, then the difference in moment ' Δm ' can be written as,

$$\Delta m = \Delta T \times Fa_2$$

$$\Delta m = \begin{bmatrix} 0 & -\Delta T_z & \Delta T_y \\ \Delta T_z & 0 & -\Delta T_x \\ -\Delta T_y & \Delta T_x & 0 \end{bmatrix} \otimes \begin{bmatrix} Fa_{2x} \\ Fa_{2y} \\ Fa_{2z} \end{bmatrix}$$

But this equation cannot be solved directly, as the cross product forms a skew symmetric matrix. Instead by taking the cross product of the difference in moment Δm and the force Fa_2 we can get the difference in moment arms.

$$\Delta r \text{ (difference in moment arms)} = Fa_2 \times \Delta m$$

Step 6: If " b " is the component of translation along the direction of force Fb_2 , then,
 $b = \Delta r \bullet fb_2$.

There is no change in the moment arm when the force translates along the line of action of the force, so the information of the amount of translation along Fa_2 cannot be recovered from the above equations. But, the component along Fa_2 can be obtained by repeating the same procedure with Fb_2 and Mb_2 . So we need data from a second face.

Step 7: Let " a " be the component of translation along Fa_2 which can be obtained by repeating Steps 1-6 with Fb_2 and Mb_2 .

Step 8: Let $Fn_2 = Fa_2 \times Fb_2$ and $Fn_1 = Fa_1 \times Fb_1$.

Step 9: Let " c " be the component of translation perpendicular to the plane containing Fa_2 and Fb_2 .

Then, $c = \Delta r \bullet fn_2$
where fn_2 is a unit vector in the Fn_2 direction, and ' Δr ' is the difference in moment arms obtained in Step 6.

Step 10: Add all the components in the Fa_2 , Fb_2 direction to get ΔR which is the actual translation involved in sensor X, Y and Z axes.

$$\Delta R = a * fa_2 + b * fb_2 + c * fn_2.$$

Step 11: The rotation involved in the orientation change can be represented by a rotation matrix ' T ' as described in Section 3.3 of this chapter. The ' T ' matrix can be obtained by solving the following three equations:

$$Fa_2 = T \otimes Fa_1$$

$$Fb_2 = T \otimes Fb_1$$

$$Fn_2 = T \otimes Fn_1$$

4. TEST BED

This chapter will explain both the hardware and the software that comprise the test bed equipment and explain the rationale behind its use. Except for the small test fixtures, no hardware has been made special for this project and most of the hardware required to carry out these experiments was originally setup by M. A. Skubic (1997). The equipment is off the shelf hardware that is commercially available. The software is a combination of commercially available, public domain, general lab software, and previous research software specifically customized for this research. The test bed will be described as two component subsystems: (1) the robot system, and (2) the haptic interface.

4.1 Robot System

The robot system used in this work was originally a part of the test bed of USARC (Universities' Space Automation and Robotics Consortium) for research in distributed telerobotics applications (Skubic, et al, 1995). Although the capabilities of the distributed network are not fully utilized here, the robot system provided a reasonable equipment base for these experiments. The equipment is located in the robotics laboratory in the Department of Computer Science at the Texas A&M University.

Figure 10: The MERLIN Robot

The robot arm is a six degree-of-freedom MERLIN manipulator built by the American Robot Corporation (MERLIN Operator Manual). Kinematically, the MERLIN is similar to the PUMA robot found in many research labs. Stepper motors, are used, however, to control the joints. The wrist is equipped with a 3- pronged gripper, which can be opened or closed by pneumatic control. Figure 10 shows a graphical representation of the MERLIN, and it is used for these experiments.

The American robot controller that comes with the MERLIN provides the joint level control of the robot for advanced control functions (e.g., Cartesian control and force control). the MERLIN controller is interfaced to a 133 MHz Pentium PC via a high speed bus-to-bus interface. The Pentium is running a real time kernel, called LynxOS (LynxOS Operator Manual), as well as a version of RCCL/RCI (JR3 and MERLIN Operator Manuals), which provides a library of functions for robotics applications and control.

A JR3 DSP-based force sensor (JR3 Operator Manual), model 67M25A-U560, is mounted on the robot wrist. Table 3 shows the manufacturer's listed capacity and resolution for this model sensor. However, the listed resolution values did not seem realistic under normal operating conditions, given a variety of potential sources contributing to sensor noise.

To get an estimate of the sensor uncertainty under realistic operating

conditions, a suite of experiments were performed using the same force sensor and robot (Skubic, 1997). The purpose of these tests was to investigate the effects of environmental factors (such as vibrations of the robot and electromagnetic interference), to observe the force sensor signals over a range of robot workspace, and to ultimately measure uncertainty values that were representative of typical operating conditions. The results of these tests are tabulated in the Technical Report titled, "Force sensor characterization," by M. A. Skubic (1997).

4.2 Haptic Interface

For the demonstration of the single ended contact formations, a device that provides haptic feedback to the human teacher as suggested by M. A. Skubic (1997) was used. For this purpose, a commercially available device called the PHANToM (PHANToM Operator Manual) is used. A 6 degree-of-freedom output is generated from the PHANToM, based on the position and the orientation of the end point connected to a pen-like stylus. A 3 degree-of-freedom input can be provided to the PHANToM, which represents the 3 components of the force delivered to the stylus tip. In this way, the PHANToM can be used as a force-reflecting hand controller to drive the MERLIN robot telerobotically. The motion of the stylus is connected via software to the end effector of the robot. The operator holds the PHANToM

Table 3: Manufacturer's Specifications and Measured Uncertainty
(Forces in N; Moments in Nmm)

	F_x	F_y	F_z	M_x	M_y	M_z
Specs: Capacity	100	100	200	6300	6300	6300
Specs: Resolution	0.0445	0.0445	0.0890	3.4	3.4	3.4
Specs: Uncertainty	0.20	0.18	0.47	17.3	16.7	16.1

stylus and moves it to the desired position. The forces from the force sensor are used as input to the PHANToM so that the operator can feel the same forces sensed by the robot.

The control program used for performing skill demonstrations is written using the RCCL library. To achieve adequate haptic feedback, the PHANToM manufacturer suggests that the force feedback loop run at a frequency of at least 800 Hz. However the timing resolution of the LynxOS operating system limits this to no faster than 100 Hz. The problem was resolved by simply letting the loop run as fast as possible. For the experiments discussed here, the PHANToM force feedback loop was running at approximately 4000 Hz. For purposes of data collection, the position and force information is sampled at a frequency of 40 Hz.

The forces sensed by the force sensor are pre-processed before they are sent to the PHANToM for haptic feedback. First, offsets are subtracted to eliminate gravitational forces. Forces are effectively nulled at the force sensor, before the demonstration process begins so that the operator feels zero force when no contact has been established. Second, small forces are ignored. Any force component less than 0.45N is ignored. Finally, the resulting force signals are run through a third order Butterworth filter and then sent to the PHANToM. The JR3 force sensor also has the capability of filtering force signals. However, adding the filter prevents the sensor from running at its maximum rate of 8 kHz and so the filtering is performed in the RCCL control program.

5. RESULTS AND CONCLUSIONS

In this thesis we looked at the affect of an orientation and position change (with respect to the sensor axes) of a grasped object, on the process of recognition of single ended contact formations. We have also formulated a method of adapting the task of recognizing a single ended contact formation after such an orientation and position change occurs. The first part of this section will present the results obtained by using this methodology. The second part will discuss the limitations of the proposed method and suggests some future extensions, which will be helpful in improving the adaptation process.

There were basically two sets of experiments conducted; one involved testing the performance of the existing fuzzy logic and neural network classifiers with an orientation and position change. And the second involved evaluating the performance of both the classifiers after adapting the classifiers with the methodology discussed in this thesis. The experimental results show that the use of the presented methodology improves the performance of the classifier in being able to successfully recognize the single ended contact formations after an orientation and position change with an accuracy close to that of the trained accuracy.

5.1 Experimental Results

In this section, we present the results of experiments designed to test the methodology. The equipment used for the experiments is described in Chapter 4. We present the experimental results in 3 parts. First, the performance of the state classifier based on fuzzy logic after an orientation and position change and before using the methodology of this thesis is discussed. Experimental results are given for 2 different data sets. Second, we present results of the

same test using the methodology of this thesis. Third we discuss results using a neural network to classify the contact formations.

(a) Performance of State Classifier Based on Fuzzy Logic

Here we present the performance of the state classifier (as proposed by M. A. Skubic (1997)) after an orientation and position change of the grasped object. Training the fuzzy logic classifier involves the generation of membership functions for each feature in each class. The membership functions are parameterized based on the means and standard deviations of the input vectors in the training set. As a result, membership function generation involves simply calculating the means and standard deviations for each feature. Figure 11 shows the normalized means for each of the 8 single ended contact formations of the square block workpiece. In Figure 11 AB, BC, CD and DA represent four faces of the square block and A, B, C and D represent the included edges as illustrated in Figure 12. Figure 13 illustrates the change in the means of the AB and BC SECF classes due to an orientation and position change. Tables 4 and 5 list the performance of the fuzzy classifier in terms of percentage recognition of the sample data for 4 edges and 4 faces (as shown in Figure 12), respectively, before and after an orientation and position change of a square block workpiece.

On analyzing the performance results presented in Tables 4 and 5 we can see that the performance degradation for the face SECFs is more than the edge SECFs. This is expected since for small orientation change some of the new force signals from the edges still lie in the original cone. But the force signal spread of the faces are much less than edges so the probability that the new force signals fall in the original spread is much less

Figure 11: The Projection of Normalized Means of 8 Single-Ended Contact Formations for a Square Blockwork Piece

Figure 12: Figure Illustrating the 8 Single-Ended Contact Formations for a Square Block Workpiece

Figure 13: Effect of Orientation Change on the Direction of the Mean's of SECF Classes

Table 4: Performance of Fuzzy Logic State Classifier after an Orientation and Position Change for 4 Edge SECF's of a Square Block Workpiece

Situation\SECF	Edge A	Edge B	Edge C	Edge D
Performance before an orientation and position change	92.3	96.7	94.2	98.1
Performance after an orientation and position change	42.0	36.5	32.7	38.3

Table 5: Performance of Fuzzy Logic State Classifier After an Orientation and Position Change for 4 Face SECF's of a Square Block Workpiece

Situation\SECF	Face AB	Face BC	Face CD	Face DA
Performance before an orientation and position change	98.9	97.2	98.1	97.7
Performance after an orientation and position change	0	5.1	0	4.3

compared to that of the edges. Tables 6 and 7 list the performance of the fuzzy classifiers before and after an orientation change for a pentagon block workpiece. In this case 10 SECFs were sampled, including five faces AB, BC, CD, DE & EA and five edges A, B, C, D and E.

The performance degradation for the pentagon is more compared to that of the square block workpiece. This is consistent with the explanation for the poor performance of the faces of the rectangle. As the number of faces and edges increase, the spread of the force/moment signals decreases so even a small change in the orientation or position can cause the new signal to lie beyond the original sets.

(b) Performance after Using the Adaptation Methodology for the Fuzzy Logic Classifiers

This section highlights the improvement that results in using the method to recognize the SECFs of the square and pentagon block work pieces described in this thesis. The classifier is adapted to the new situation by modifying the original classifier data consisting of the trained means and standard deviations as described in Chapter 3. Tables 8 and 9 list the percentage recognition and improvement percentage of the fuzzy state classifier for the square block workpiece after the adaptation.

Table 6: Performance of Fuzzy Logic State Classifier after an Orientation and Position Change For 5 Edge SECFs of a Pentagon Block Workpiece

Situation \ SECF	Edge A	Edge B	Edge C	Edge D	Edge E
Performance before an orientation and position change	90.3	91.7	89.4	88.9	90.5
Performance after an orientation and position change	0	0	2.8	0	0

Table 7: Performance Of Fuzzy Logic State Classifier after an Orientation and Position Change for 5 Face SECFs of a Pentagon Block Workpiece

Situation \ SECF	Face AB	Face BC	Face CD	Face DE	Face EA
Performance before an orientation and position change	90.3	91.7	89.4	88.9	90.5
Performance after an orientation and position change	0	0	0	0	0

Table 8: Performance of Fuzzy Logic State Classifier after Adaptation to an Orientation and Position Change for 4 Face SECFs of a Square Block Workpiece

Situation \ SECF	Face AB	Face BC	Face CD	Face DA
Performance before adaptation	0	5.1	0	4.3
Performance after adaptation	92.1	90.9	93.4	94.2
Improvement in performance over the original classifier	+92.1	+85.8	+93.4	+89.9

Table 9: Performance of Fuzzy Logic State Classifier after Adaptation to an Orientation and Position Change for 4 Edge SECFs of a Square Block Workpiece

Situation\SECF	Edge A	Edge B	Edge C	Edge D
Performance before adaptation	42.0	36.5	32.7	38.3
Performance after adaptation	94.0	92.4	89.2	90.8
Improvement in performance over the original classifier	+52.0	+55.9	+56.5	+52.5

Table 10: Performance of Fuzzy Logic State Classifier after Adaptation to an Orientation and Position Change for 5 Edge SECFs of a Pentagon Block Workpiece

Situation\SECF	Edge A	Edge B	Edge C	Edge D	Edge E
Performance before adaptation	0	0	2.8	0	0
Performance after adaptation	85.4	88.1	90.5	87.1	89.0
Improvement in performance over the original classifier	+85.4	+88.1	+87.7	+87.1	+89.0

Table 11: Performance of Fuzzy Logic State Classifier after an Orientation and Position Change for 5 Face SECFs of a Pentagon Block Workpiece

Situation\SECF	Face AB	Face BC	Face CD	Face DE	Face EA
Performance before adaptation	0	0	0	0	0
Performance after adaptation	89.8	90.3	88.8	89.5	89.6
Improvement in performance over the original classifier	+89.8	+90.3	+88.8	+89.5	+89.6

Tables 10 and 11 list the percentage recognition and improvement percentage of the fuzzy state classifier for the pentagon block workpiece after the adaptation. The pentagon block workpiece has 10 data sets 5 for each of the faces and 5 for each of the edges.

The results presented in the preceding tables were obtained by modifying the classifier data file. The modification is successful since the fuzzy classifier depends on means and standard deviations. The new means and standard deviations can be easily determined for the new situation because they behave exactly like the rest of the force signals.

(c) Performance after Using the Adaptation Methodology for the Neural Network Classifiers

The training of a neural network involves figuring out the ideal set of weights in each of its neurons or nodes. So a trained neural network performance depends on those weights. There is no direct relationship to weights obtained by training and physical entities like the means and standard deviations, so for a neural network to be able to adapt to the new situation, retraining is required. We can still take advantage of knowing the translation and rotation involved in new situation. Instead of collecting a new set of data we can simulate the data in the new situation by applying a reverse transformation on the original data sets. So in

Table 12: Performance of a Neural Network State Classifier after Adaptation to an Orientation And Position Change for 4 Face SECFs of a Square Block Workpiece

Situation \ SECF	Face AB	Face BC	Face CD	Face DA
Performance before adaptation	0	0	0	0
Performance after adaptation	94.1	97.3	92.6	95.1
Improvement in performance over the original classifier	+94.1	+97.3	+92.6	+95.1

this way we can efficiently adapt a neural network based recognition tool. Table 12 lists the results of adapting the neural network based classification.

The methodology followed in this thesis helps in reducing the amount of training data required. This is achieved by adapting the data collected in the earlier to a new situation. The adaptation algorithm as implemented in this thesis requires force and moment data for any two perpendicular faces to adapt the classifiers and the previous data to the new situation. The Table 13 shows the average number of sample data points collected for successful (classification success rate above 90%) implementation of the classification process. The data was collected

at a frequency of 50Hz during different contact formation. To provide a controlled setting, the workpiece was held in a stationary configuration by the robot arm while a flat plate (the environment) was moved manually to simulate the possible contact formations. A minimum of 1000 data samples resulted in good classification performance (classification success rate above 90%). This number of 1000 samples was observed in the experiments conducted during this research. The number of data samples can be less than this figure as long as they result in an accurate representation of the spread of the force and moment vectors resulting in a contact formation.

Table 13: Average Number of Data Samples Collected for a Square Block Workpiece for Successful Classification

Situation\SECF	Face AB	Face BC	Face CD	Face DA	Edge A	Edge B	Edge C
Number of samples required for a good classification using the original algorithm	1432	1583	1219	1093	1409	1356	1081
Number of samples collected for successful classification using the adaptation process	1534	1397	0	0	0	0	0

6. FUTURE WORK

The experimental results show that the research objectives have been successfully met, but there is much more work to be done and there are some limitations to this method. This method does not take into account the effect of gravity. These effects were very small for the objects used in this research, but as the size of the object increases and for large orientation and position changes the effect of gravity can no longer be ignored. This research assumed that the grasped objects are rigid bodies. The flexibility of the object also affects the contact recognition task.

We would want to make the adaptation procedure more automated by implementing a system which automatically collects data in the new situation and determining the required transformations.

Hybrid methods can be developed wherein the translation and the rotation data obtained by the methodology followed in this research is used to simplify or add more information to the position/geometric based approaches. We would also want to generate a contact recognition tool that can determine the curved surface contact formations.

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