Neuro-Fuzzy Control of Robotics Peg-in-Hole Insertion

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Abstract

A heuristic method is developed to control the automatic peg-in-hole insertion process. The approach is based on Adaptive Spline Modelling of Observed Data (ASMOD) which constructs an approximate model for a system. To improve the performance of this model, some manual observations of the empirical data are also incorporated into the control algorithm. The performance of the developed algorithm is demonstrated through experimental work. The results have shown 100% success rate in the insertion process.

1 Introduction

Achieving automated peg in hole insertion has been the focus of many research activities. The popularity of this method stems from the fact that it provides a simple means of replicating many of the systems involved in machine part assembly using a robotics system. In order to automatically control the peg insertion it is necessary to model the process and use this model to control the robot.

Conventional control techniques involve producing mathematical models to represent the system and then using these models as a basis of controlling the system. These mathematical models are generally built from first principles such as conservation of energy or mass with complexity then added. For non linear time variant systems such as peg in hole insertion it is extremely difficult to produce accurate mathematical models and the computational complexity of any such models is great.

An alternative approach is to use heuristic methods to produce a system model. This method involves using experimental data to produce an approximate model of the system. The experimental data consists of information obtained whilst the task is performed by an expert human operator.

In this work a neuro-fuzzy method is developed to control the operation of a robotics system developed for the peg in hole insertion process.

The work consists of a number of stages and facets. In the first stage a robotics system has been designed to perform the peg-in-hole insertion. This new design is optimised to perform the peg in hole insertion process with as little passive compliance as possible whilst maintaining as simple a design.

The ability to design a control scheme for the system, solely from empirical data with no prior expert knowledge or mathematical analysis is investigated. For this purpose a heuristic algorithm called Adaptive Spline Modelling of Observed Data (ASMOD) which constructs an approximate model for a system. To improve the performance of this model some manual observations of the empirical data were also incorporated into the controlling program. The developed algorithm has produced a 100% insertion success rate.

The performance of the developed algorithm is demonstrated through experimental work. The results have shown 100% success rate in the insertion process.

In the course of the paper a review of the previous work in this area will be carried out. The robotics system designed for the study will be described and the neuro-fuzzy control algorithm developed will be introduced. The performance of the developed system will be finally demonstrated and some conclusions will be drawn.

2 Background

Research into the peg in hole insertion can be grouped into 2 primary categories; passive and active compliance control. Compliance refers to an object's characteristic to deform (bend and twist) in response to the external forces applied to the object. A human operator easily performs compliant motion by using the inherent senses of touch and sight whilst performing manual assembly. This is difficult to replicate in robot motion.

Passive compliance control concentrates on either incorporating elasticity or flexibility into the object (in this case the peg) or applying random external forces (vibrations) to the object in order to overcome irregularities or errors in the system.

Active compliance concentrates on monitoring the assembly process via transducers. The information received is analysed and from this the corrective action required for the process to continue is determined. The methods of active compliance may be grouped according to the type of transducer used.

In order to provide accurate repeatable control using active compliance, the system must be as rigid as possible (i.e. no passive compliance). This ensures the readings reported by the transducers remain accurate whilst the data is being processed.

The most successful implementation of passive ompliance to achieve the peg in hole insertion is the Remote Centre Compliance (RCC) wrist developed by then Charles Stark Draper laboratory [Whitney and Nevin 1979]. This system uses the external forces encountered by the peg when contact with the hole occurs to alter the peg's relative displacement and to reduce the misalignment between peg and hole. The advantages of this system are that it is relatively inexpensive and no signal processing or feedback sensor is required. The disadvantages include [Qiao et al 1995] [Vukobratovic and Stokic 1989] [Ranky and Ho 1995]:

- It can only operate with chamfered parts.
- They are not flexible enough to be switched from one task to another.
- The maximum displacement is restricted to the size of the chamfers used.
- The system is susceptible to vibrations of the peg.
- Greater force is required to insert the peg.

Another common method of passive compliance is the use of vibratory motion [Qiao et al 1995]. In this method, in order to overcome the initial misalignments or irregularities, the peg is subjected to random vibrations as it is inserted. This approach was the focus of research by Oshisi et al [Ohishi et al 1985]. The results for this method are mixed and are very much dependent on the initial displacement and the magnitude - direction of the vibration. As these factors cannot be easily measured, correct insertion is difficult to achieve in a short time frame [Qiao et al 1995].

The application of force/torque control has been by far the most popular approach for achieving active compliance control of the peg-in-hole insertion.

A force-torque sensor is placed between the work piece (peg) and the robot arm gripper. During the insertion process, the external forces and torques applied to the peg are measured and if found to be above predetermined maximum values, corrective action is taken to reduce these values before inserting the pin further [Nguyen 1996]. The different methods of force/torque control vary in the way the force/torque information is processed in order to determine the corrective action required. As the process is extremely difficult to model mathematically, a number of different methods have been applied to produce accurate system models. The majority of research in this field study different modelling techniques and examine their suitability to control real time applications.

An extension of the force/torque technique is force/position control. This technique incorporates the absolute position of the peg into the control algorithm or model [Ranky and Ho 1995].

In the previous work of this research group [Naghdy and Nguyen 1998] fuzzy logic was used to achieve active compliance control of the peg in hole insertion process. The employed fuzzy rule-base was developed by empirical means. The insertion of the peg by a human operator was observed and from this, simple rules of thumb were derived. These rules were the basis for the fuzzy rule-base. The results obtained in this work demonstrated the suitability of fuzzy systems for the control of the peg-in-hole insertion.

The project reported in this paper is an extension of the precious work.

3 Heuristic Modelling of System

The traditional control techniques utilise the mathematical model of a system constructed from the physical properties of the process. These models commence with basic first principles such as conservation of mass and energy and complexity is added as the model is refined. However, as the process to be controlled becomes more complex, the mathematical models begin to exhibit non-linear and time varying properties. Thus deriving an accurate mathematical models based on the physical properties of the process becomes increasingly difficult and computationally demanding.

An alternative approach to produce the model of a system is to use empirical data as the basis of constructing the model. Heuristic or self-learning algorithms are often employed to process the empirical data and construct an accurate system model. These algorithms attempt to interpolate or approximate the observed data. Refinement and accuracy is added as they are processed. The pursuit of an optimal heuristic algorithm is currently a major research focus.

The most popular types of heuristic algorithms are Artificial Neural networks, Fuzzy logic and expert control. Each of these systems may be implemented using different modelling algorithms which possess their own advantages and disadvantages [Brown and Harris 1994].

A major disadvantage of many of the modelling algorithms is that the complexity of the model grows exponentially with the dimension of the input data. This property makes many of the algorithms unsuitable for real time applications such as the peg in hole insertion where computation time is critical. One algorithm which does exhinit such shortcoming is the Adaptive Spline Modelling of Observed Data (ASMOD) method [Kavli and Weyer 1995]. This algorithm has been employed in this work to model the insertion process.

The ASMOD algorithm provides a means of automatically building a system model utilising observed data. ASMOD employs B-splines to represent general nonlinear and coupled dependencies in the observed input data [Kavli and Weyer 1995].

3.1 B-Splines

B-splines have been widely used as basic surface fitting elements in graphical applications for the last twenty years [Brown and Harris 1994]. A B-spline network falls into the group of Associative Memory Networks. A B-spline function is simply a piecewise polynomial mapping, which is formed from a linear combination of basis functions [Brown and Harris 1994]. A multi-dimensional B-spline model is the tensor product of univariate or one dimensional models and it is thus sufficient to describe the one dimensional model and generalise to multidimensional models [Shahri and Naghdy 1996]. A one dimensional B- spline is comprised of a linear combination of basis functions and may be expressed by :

$$s(x) = \sum_{i=0}^{L-1} c_i b_i(x) = c^T b(x)$$

Where:

$b(x)=(b_0(x), b_1(x),.....,b_{L-1}(x))$ represents the basis functions, the coefficient vector $c=(c_0, c_1, ...,c_{L-1})^T$ represents the set of parameters that are to be estimated when fitting the model to data, and the parameter L represents the number of degrees of freedom of the model.

B-spline basis functions provide a convenient means of representing piecewise polynomial mappings [Boor 1978]. Each basis function is univariate and is a composition of a set of polynomials of a given degree p, each defined over sub-intervals of the input space (knots). The degree of the basis functions determines the smoothness of the model output (larger the order the smoother the output). A knot vector t comprised of an ordered sequence of real numbers is used to uniquely define the set of basis functions in a B-spline model. The basis functions are thus defined from the knot vector as below [Shahri and Naghdy 1996]:

For a basis function of degree zero

$$b_{i,0}(x)=\begin{cases}1, t_i \le x \langle t_{i+1}\\ 0, otherwise\end{cases}$$

For degrees (p=1,2,.....)

$$b_{j,p}(x)=\frac{x-t_j}{t_{j+p}-t_j}b_{j,p-1}(x)+\frac{t_{j+p+1}-x}{t_{j+p+1}-t_{j+1}}b_{j+1,p-1}(x)$$

Examples of linear and quadratice basis functions are shown in Figure 1.

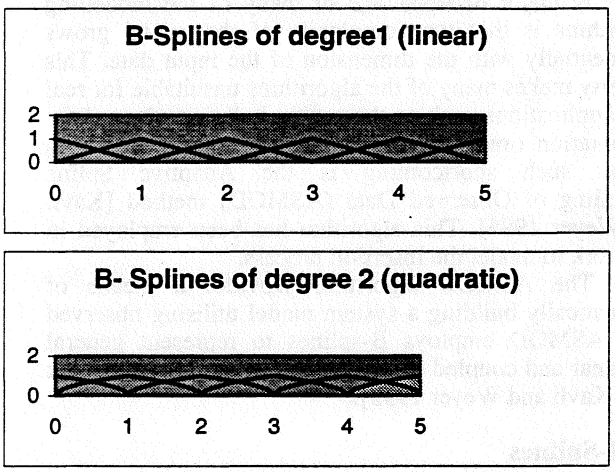

Figure 1- Basis Splines formed by the Knot Vector n = (0,1,2,3,4,5)

The above demonstrate how the output becomes smoother as the degree of the basis function polynomials is increased. Also on each interval p coefficients are required for each polynomial and p basis functions contribute to the output.

Comparison of the above basis functions with fuzzy membership functions (Figure 2), shows similarity between them. This enables the B-spline networks to be interpreted as a set of fuzzy rules.

The weights or coefficients of a B-spline network may be trained iteratively using a range of LMS type learning rules[Brown and Harris 1994]. This self training process combined with the inherent accuracy of B-splines for modelling data makes it possible to accurately model the observed data. The B-spline models suffer from a so-called curse of dimensionality [Kavli and Weyer 1995]. This arises from the fact that the model complexity grows exponentially with the number of input variables. It can be shown that if k univariate basis functions are defined for each axis and the input dimension equal to n the then k^n parameters are required [Brown and Harris 1994]. This property makes B-splines unsuitable for modelling systems with more than a few input variables. The ASMOD algorithm overcomes this curse of dimensionality and is discussed in the following section.

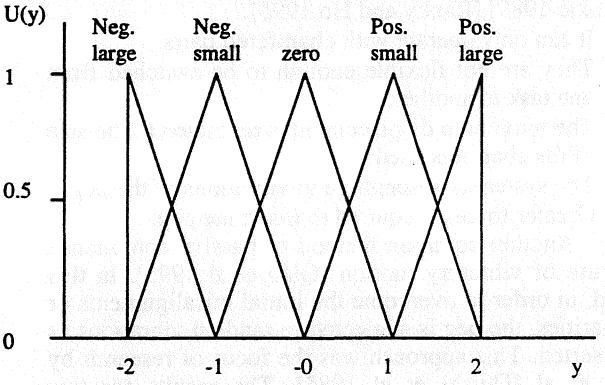

Figure 2 - Typical Fuzzy logic Rule Base

3.2 ASMOD Algorithm

The ASMOD algorithm takes advantage of the fact that for high dimensional data modelling problems the data can often be modelled as a sum of low dimension sub models. For a model with 8 basis functions along each axis and 10 input dimensions, a conventional B-spline model would require 8^{10} parameters. Modelling this data as a sum of two dimensional sub models the number of parameters could be reduced to 320 ($8^2+8^2+8^2+8^2+8^2$). Figure 3 demonstrates the ASMOD algorithm utilising this property.

ASMOD also determines strong correlation between input variables and utilises these properties to remove variables that contribute little to the model performance or accuracy.

The ASMOD model is represented as a sum of U low dimensional B-spline models called sub-models.

$$y(x)=\sum_{u=1}^{U} s_u x(u)$$

These sub models are denoted by $\{s_u(x_u)\}$. x_u represents the input vector and satisfies the property $\bigcup_{u=1}^{U} x_u \subseteq x$. Thus an input variable can appear in only one of the sub models.

If the weight coefficient vector for each sub-model is denoted by $w_u, w=\bigcup_{u=1}^{U} w_u$, and the basis function output vector by $a=\bigcup_{u=1}^{U} a_u$ the model output may be expressed by:-

$$y(x)=\sum_{i=11}^{p} a_{i(x)w_i}$$

The above expression is identical as that given previously for a B-spline network however, the number of weights

required is greatly reduced and thus the overall complexity is also reduced. The fact that the ASMOD model is a linear combination of B-splines, combined with the similarity of B-spline basis functions and fuzzy logic sets indicates that the ASMOD algorithm may provide a means of automatically determining a fuzzy rule base and membership functions from the observed data without any in depth analysis or expert knowledge of the system.

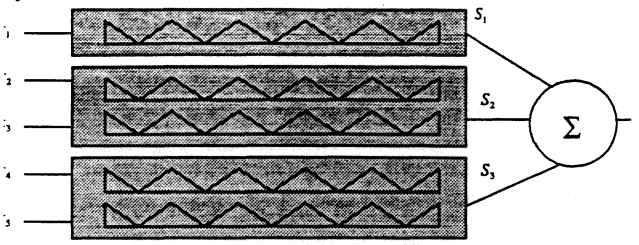

Figure 3 - The ASMOD Algorithm Structure

4.0 Experimental Rig

The experimental rig developed to implement the developed control algorithm is shown in Figure 3. As the host P.C. must control all the system hardware, it is virtually impossible to achieve a constant sample rate for a PID loop constantly controlling the motor. The designed control system overcomes this problem by utilising a cascaded control structure. The position control loop is only active during a change in the peg's position. Thus a constant sample rate is more easily achieved during this action. The internal speed loop acts as a regulator system during periods when the peg is stationary, providing the force required to maintain the peg's current position. To allow successful implementation of this system, the P.C. interface board must maintain its analogue output at the value last requested by the P.C.

The rig developed provides an extremely rigid and accurate system with a much faster response time than the one used in the previous work. The acceleration, velocity and trajectory of the peg are easily controlled by the PC.

5.0 Experimental Procedure

In order to obtain the experimental data required to construct the system model, the experimental rig was operated manually by a human operator. The rig was operated in a number of different configurations, including:

- The manual correction using visual determination of error.
- The manual correction using the sense of touch with eyes closed.
- Disconnecting the hole from the driving gearboxes thus allowing free operation and then driving the peg at a constant rate and allowing the hole to realign itself. This process was only possible for very small initial displacements.

The above procedure was repeated a number of times for different initial displacements. The force/torque data, the peg vertical position and the angular misalignment about each axis were continually recorded for each insertion.

4.1 System Modelling

In order to successfully control the peg in hole insertion, the angular displacement about both the X and Y axes must be known or accurately estimated. It is also advantageous to know the maximum distance that the peg can be inserted at any given time without causing excessive force or jamming. Hence it was necessary to construct models that would accurately estimate X and Y displacements and the next vertical position of the peg.

Since ASMOD models are single output, a separate model for each of the outputs was required. A block diagram of the I/O configuration for each ASMOD model is shown in figure 4.

The manual insertion data obtained in this process was used to construct a set of models for each of the insertion methods. The models were then individually tested for accuracy using the test data that had not been used in the construction of the model.

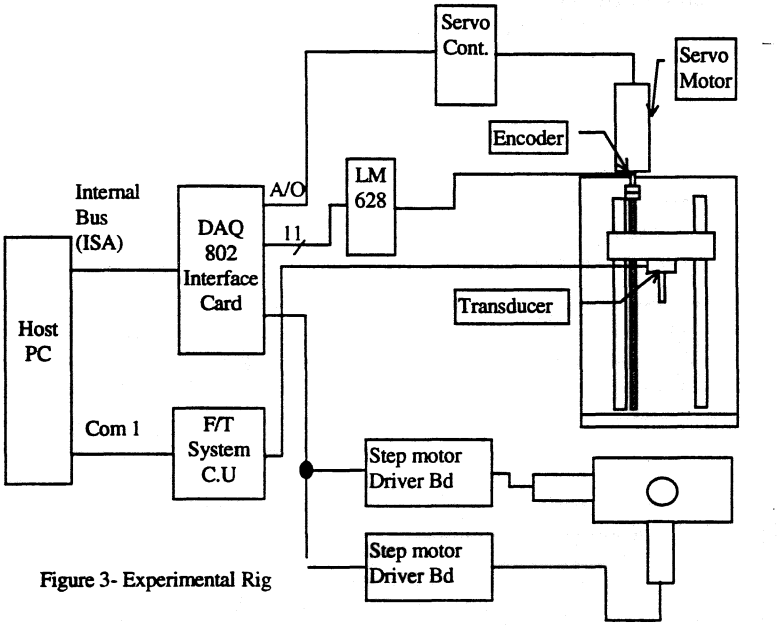

Figure 3- Experimental Rig

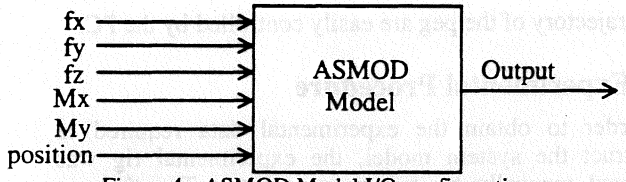

Figure 4 - ASMOD Model I/O configuration

The modelling process was continually repeated using varying basis spline degrees and optimisation criteria. The accuracy of each model was compared to that of the best previous model with the results recorded.

The models produced using the data recorded when the human operator carried out the insertion purely by his/her sense of touch proved very inaccurate. These poor results were attributed to the difficulty in inserting the peg via this method. This arose from the fact that the vertical motion of the peg was driven by a lead screw mechanism which provides very little force feedback to the operator due to the large mechanical gain produced by such a system. Due to this inaccuracy it was decided not to develop this method further.

The models produced using both of the remaining data sets were quite inaccurate for each output and it was decided to concatenate the data from both methods. This produced a training data set of approximately 4000 samples over 30 insertions. These results were improved over all previous results. Howeve, the models obtained for angular displacement about X and Y axes were not accurate enough to achieve automated insertion.

In order to improve accuracy, it was decided that more test data was required. This was obtained by carrying out a further 20 manual insertions. The data from these insertions was then concatenated with that all ready gathered previously. The training data now consisted of approximately 7800 samples or 50 manual insertions. The modelling process with varying basis spline degrees and optimisation criteria was again repeated using this data.

The constructed models were tested on line to calculate the angular displacement about each axis and thus control the insertion process. It should be noted that at this stage the vertical motion was not controlled by the ASMOD model for this output but was incremented in small steps of constant size.

The initial tests showed that approximately 30 percent of insertions were not satisfactory due to excessive errors or jamming.

In order to improve the performance of the developed models, it was decided to enhance the rule-base and hence the control algorithm by adding some empirical rules constructed by observing the behaviour of the system. This approach improved the performance of the system to a success rate of about 100%.

4.2 Results

The finalised heuristic control scheme was used to control the experimental rig. The peg was inserted at different initial angular misalignments between the peg and the hole. These misalignments were achieved by rotating the hole from its neutral position (i.e. The position where the peg can be inserted fully into the hole with no corrective action) about both the X and Y axes. A positive angle represents a clockwise rotation about the axis.

For each insertion, the insertion time, number of program iterations, X and Y model corrections and incorrect model actions amended were recorded. The number of program iterations is included to allow an unbiased means of comparing the insertion speed of different attempts.

The results of the insertion process using combinations ±4.5 degrees are shown in table 1. The amount of 4.5 degrees represents approximately 500 steps (0.009 degrees/step) of the stepper motors used for both X and Y axes and also represents a very large initial displacement for the insertion process. It is assumed that in practice, at least this amount of accuracy can be achieved in the approach phase by a means of simple proximity control.

The vertical force readings and corrective actions of trial number 1 in table 3 above are detailed in Figure 5 below. The force reading is measured in uf (unit force), where 1uf corresponds to approximately 0.056N.

5. Conclusion

The design and development of a heuristic control system for the automatic-peg-in-hole insertion was reported in this paper.

The model used in the control system was

Trial Number	X axis Misalignment in degrees	Y axis misalignment in degrees	Insertion time in seconds	program Iterations	X model actions	Y model actions	X model program corrections	Y model program corrections
1	-4.5	-4.5	180	720	58	24	0	0
2	-4.5	4.5	200	708	57	21	11	9
3	4.5	4.5	240	680	45	18	0	17
4	4.5	-4.5	220	764	79	8	30	0
5	4.5	4.5	190	651	36	18	6	9
6	-4.5	-4.5	166	639	33	1	23	0
7	-4.5	4.5	158	640	33	7	7	1
8	4.5	4.5	172	578	42	3	4	1
		Average Values	190.8	639.0	47.9	12.5	10.1	4.6

Table 1 - Results of heuristic method

derived from the input/output pairs produced from the system using ASMOD method. This model was further enhanced by including the rules obtained by observing the behaviour of the system.

The designed heuristic system proved to be a reliable control system for the-peg-in-hole insertion process. The system produced a 100% insertion success rate for all of the initial misalignment angles tested. This is in contrast with the Fuzzy logic controller developed in the previous work [Naghdy and Nguyen 1998] which achieved an overall insertion success rate of 46%. The success rate for the previous Fuzzy system decreased dramatically as the initial misalignment increased and achieved only 22% success for initial angles of ±4.5 degrees. On the contrary, the system developed in this work maintained its high success rate even for high initial misalignments

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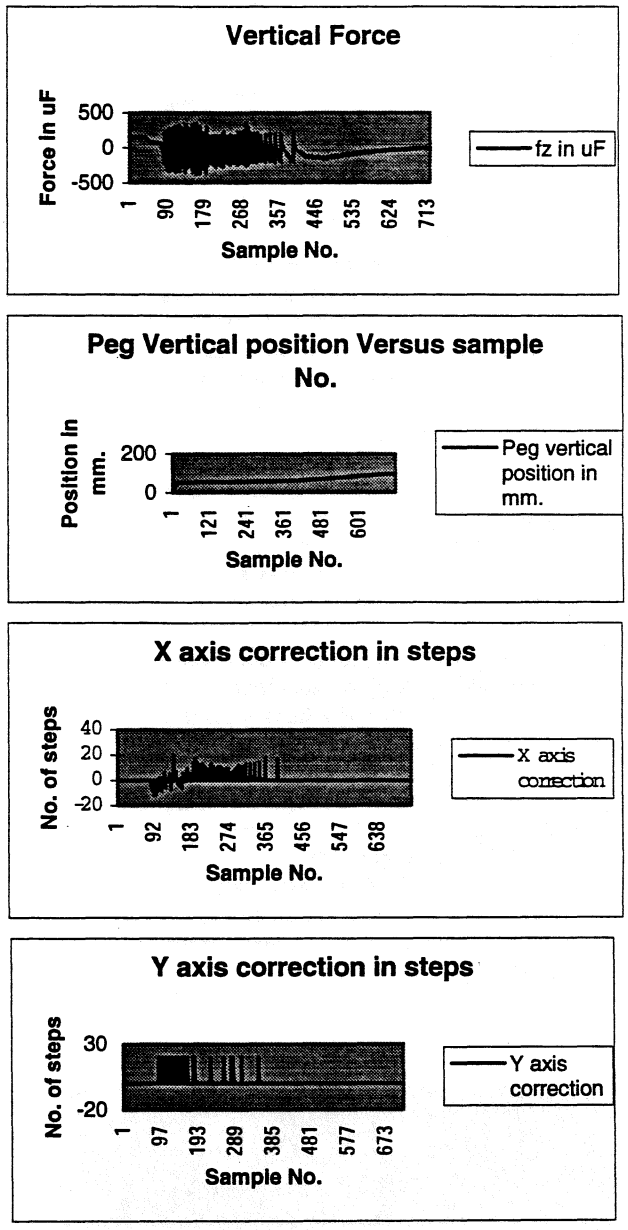

Figure 5- Results of Heuristic Method