



UNIVERSITI PUTRA MALAYSIA

**DEVELOPMENT OF ARTIFICIAL INTELLIGENT TECHNIQUES FOR
MANIPULATOR POSITION CONTROL**

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By

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Faculty: Engineering

Inspired by works in soft computing this research applies the constituents of soft computing to act as the “brain” that controls the positioning process of a robot manipulator’s tool. This work combines three methods in artificial intelligence: fuzzy rules, neural networks, and genetic algorithm to form the soft computing plant uniquely planned for a six degree-of-freedom serial manipulator. The forward kinematics of the manipulator is made as the feedforward control plant while the soft computing plant replaces the inverse kinematics in the feedback loop. Fine manipulator positioning is first achieved from the learning stage, and later execution through forward kinematics after the soft computing plant proposes inputs and the iterations. It is shown experimentally that the technique proposed is capable of producing results with very low errors. Experiment *A* for example resulted the position errors on px : 0.004%; py : 0.006%; and pz : 0.002%.



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**MEMBANGUNKAN TEKNIK-TEKNIK CERDIK BUATAN UNTUK
KAWALAN KEDUDUKAN BAGI MANIPULATOR**

Oleh

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Kajian ini menggunakan elemen-elemen dalam *soft computing* sebagai “otak” yang menentukan bagaimana koordinat akhir bagi manipulator robot dicapai. Dengan gabungan tiga kaedah dalam cerdik buatan iaitu peraturan-peraturan *fuzzy*, rangkaian neural, dan algoritma genetik mewujudkan unit *soft computing* yang disulam khas untuk manipulator robot bersiri. Kinematik terus bagi manipulator ini dijadikan sebagai kawalan suapan-terus dan unit *soft computing* menggantikan kinematik songsang dalam suapan-semula. Kejituan dalam menentukan koordinat akhir berlaku dengan melalui proses pembelajaran dan kemudian dengan kinematik terus setelah unit *soft computing* “mencadangkan” input dan iterasi. Hasil ujikaji menunjukkan bahawa teknik yang diperkenalkan ini berupaya untuk memberi hasil yang memuaskan. Ini dapat dilihat dalam eksperimen *A* di mana ralat-ralat pada px : 0.004%; py : 0.006%; dan pz : 0.002%.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
AI	Artificial Intelligent
BI	Biological Intelligent
BISC	Berkeley Initiation for Soft Computing
C	Candidate
Ch	Child
COA	Centre of Area
COG	Centre of Gravity
DH	Denavit-Hartenberg
DI	Defuzzification Interface
DK	Direct Kinematics
DKP	Direct Kinematics Plant
DOF	Degree-Of-Freedom
DR	Dynamic Representation
DU	Decision-Making Unit
EP	Experimental Position
Eqn	Equation
Exp	Expression
FC	Fuzzy Control
FI	Fuzzy Interface
FK	Forward Kinematics
FL	Fuzzy Logic
FLP	Fuzzy Logic Plant
FR	Fuzzy Rule
FW	First Wave
GA	Genetic Algorithm
GAP	Genetic Algorithm Plant
IK	Inverse Kinematics
KU	Knowledge Unit
LV	Linguistic Variable
Neglarge	Negative Large
Negsmall	Negative Small
NN	Neural Network
NNP	Neural Network Plant
Normal	Normal
Poslarge	Positive Large
Possmall	Positive Small
PR	Probabilistic Reasoning
SC	Soft Computing
SCP	Soft Computing Plant
SW	Second Wave



LIST OF SYMBOLS

q	Joint Angle
d	Distance
x	x -axis
y	y -axis
z	z -axis
A_i	DH Transformation Matrix
T	Homogeneous Transformation Matrix
R	Rotation Matrix
ϕ, φ, θ	Angles
μ	Fuzzy Membership Function
y^{crisp}	Function of Defuzzification
sup	Supremum
S	Weighted Sum
px	Position on x -axis
py	Position on y -axis
pz	Position on z -axis
$\lfloor p \rfloor$	Floor Value of p
$\lceil p \rceil$	Ceiling Value of p
\mathcal{R}	Real Numbers
\in	Membership
f, g, h	Mapping functions
M	Marriage function
$ M $	Cardinality of M
$ LV $	Absolute Value of LV
\cup	Union
\cap	Intersection
Σ	Summation



CHAPTER I

INTRODUCTION

1.1 Introduction

Robots nowadays have more complex plants as compared to those robots typically found in the last twenty years. Robotics itself is a broad field which a cluster of robots is referred to as industrial robots, and there is also another cluster of robots referred to as display robots that are typically found in motion pictures and theme parks. Whether it is a display-type robot or an industrial-type robot the main goal for implementing robots or creating robots is to emulate the ability of bio-mechanical systems performing very complex tasks. This emulation leads to the design of highly complicated mechanical systems whose abilities to performing tasks with very efficient kinematics and dynamics models. With this it is sufficient to emulate the capability of bio-mechanical systems such as the human arms.

A robot utilises a programming language as a platform that allows programmers to execute manipulations conforming to end users' requirement. There are different types of programming languages, but there is seen a need for intelligent behaviour where a robot is able to make simple decision to achieve a complex task. For example, a robot may be pre-programmed to function safely in handling explosives. Any external interference or foreign interventions come about the save perimeter from the robot, it can decide to response to these inferences or interventions by following a prescribe guidelines.

In fact, Mason (1998) inferred that at present, robots are unable to reason about physical processes, robot motions have to be pre-programmed in complete detail. As a result, robots are extremely limited in the tasks they can perform. They are clumsy, virtually blind, and cannot react to unexpected events.

Robot manipulators are heterogeneous controlled plants. In a well-structured industrial setting, the robot manipulator is subjected to structured, and unstructured uncertainties. The structured uncertainties include inaccurate measurement of length, mass and inertia of the robot manipulator and motor torque constants. The unstructured uncertainties include neglected high-order modes of the manipulator and non-linear friction.

Existing robot arm control systems use a simple joint servomechanism. The servomechanism approach models the varying dynamics of a manipulator inadequately because it neglects the motion and configuration of the whole system of the whole arm mechanism. Changes in the parameter of the controlled system are significant enough to render conventional feedback control strategies ineffective. The result is reduced servo response speed and damping, limiting the precision and speed of the end-effector. This makes it appropriate only for limited-precision tasks. As a result, manipulators controlled this way move at slow speeds with unnecessary vibrations. Any significant performance gain in this area of robot arm control require the consideration of more efficient dynamic models, sophisticated control techniques, and the use of computer architectures.

1.2 Statement of Problems

Manipulation is the action performed by a robot. This action includes touching, grasping, pushing and pulling, carrying objects, and moving around a rigid body. If all robot controls were precise, all objects were rigid, and all sensors were reliable, then manipulation would be a simple matter of force control. However, none of these ideal conditions hold true in the real world. In situations where a robotic system will have to interact with dynamic environments as mentioned by Berlanga *et al* (2002), the robot itself must be able to adapt to changes in such environments. On the other hand, Song *et al* (2002) describe that a robotic system is often subjected to unexpected situations due to unpredictable working conditions and payload variations. In order for robots to perform effective manipulation and locomotion, concepts in this area must include control theory, dynamics models, sensor integration, decision-making under uncertainty, solid modelling, path planning, physics of friction and grasping, the design of clever and effective mechanisms, and able to learn and make changes to deal with unexpected situations.

1.3 Objectives of Study

The main objective of this study is to bring manipulation actions to ideal conditions. However, due to advances of existing control methods such as techniques in artificial intelligence (AI) and the emergence of new control techniques such as the combination of AI called soft computing (SC) it is seen that there are possibilities of improving effective manipulations. Moreover, with high computer processing capability and with newly developed applications software fast computation is readily available for accurate and quick solutions. This is advantageous when multiple systems of equations desired to be solved; as such, analyses for precise solutions in a mechanical

system must be mathematically approached. The nature of this work involves solving analytical mechanics and AI techniques funnelled to serial manipulators. Hence, the objectives of this work are to:

- a) obtain the kinematics representation of a serial manipulator (RX-90),
- b) develop fuzzy representation,
- c) obtain neural network representation,
- d) develop algorithm for genetic unit,
- e) network AI units (fuzzy, neural network, and genetic),
- f) fuse AI with robot kinematic representation,
- g) evaluate the outcomes of this fusion.

1.4 Scope of Study

In particular, the target of this work is to investigate the use of SC in manipulator positioning. It is done with minimal use of hardware for experimentation due to inadequate expertise in this field where experimental on an actual system could not have been done. The initial process of this work is to understand the fundamentals of manipulation of serial manipulators. This includes several types of industrial robots such as the Staubli RX-series specially the RX-90. In addition, this research is designed to only study serial manipulators. Problems in parallel manipulators are out of the scope of this study. Some of the RX-90's technical specifications are not available to the public, hence this create some limits while investigating problems on its manipulation.

Due to this fact, a small number of assumptions has had been made in order to obtain information in regard to this work. Careful decisions were carried out when deciding for assumptions for unavailable technical information's of RX-90. These

assumptions are deemed relevant and reliable to this work, which is a superficial-type research. Any assumptions made are declared in related chapters. Formulations in robot dynamics and soft computing are referenced from selected resources. These resources are listed in the bibliography. Related formulations are assembled in a cluster, which is referred to as clusters of formulations. The clusters are of robot arm dynamics, fuzzy logic, neural networks, and genetic algorithm. The general groups are referred to as the robot manipulation and the soft computing technique. Robot arm dynamics belong to the group robot manipulation, and the rest belong to the group SC. All formulations are taken as they are with some modifications made to suit the research requirement and the situations. Any modifications made to the formulations are declared in related chapters.

1.5 Summary

Living creatures are fundamentally capable of fine positioning the touch and also capable of setting the degree of force on that touch. This is possible because living creatures possess brains, which are the central controllers invincible by human technologies. Bio-mechanical systems able to perform tasks such that some of these tasks are very difficult to robots. Although Nissan has produced a walking humanoid robot, but indeed this robot has limitations to emulate a human in terms of complete autonomy in decision makings, fast response to environment changes, emotion, mood, and many more humans' characteristics.

On the other hand, works in artificial intelligence has shown a great achievement where techniques in this field undeniably able to accomplish some intelligence. Using the technique in AI that is the SC it is expected that this study leads to eventual

capability for robot autonomy specially in decision makings. This work exhibits the employment of soft computing in controls, which realises manipulation effectiveness.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

Robotics has been widely utilised in the industrial settings, being taught in educational institutions, applied at research and development centres more intensively beginning the seventies although if the history of robotic is traced back to mid-1700's, J. de Vaucanson built several human-sized mechanical dolls that played music. Differ to that of robots built in the eighteenth and nineteenth century, present robots are controlled by means of electrical and electronic technology equipment and instrumentation.

Robotics encompasses of several fields of science and technology. A new generation of robots are expected to be more intelligent than the present robots where they can plan their own action, perceive and analyse their environment, and interact at high levels of abstraction with human controllers. It is possible that robotics engineering will stand on its own as a distinct engineering discipline in the future.

General views of robots are that they do things better and more efficiently, work in dangerous places, and imagine new things and future events. While basic intelligent robotic capabilities are perception that the ability to sense its own state and that of its environment, and to interpret this data and assess its significance; cognition that includes all kinds of numerical and symbolic reasoning that a robot needs to perform task intelligently; manipulation that the actions perform by a robot. Overall topics in

robot system integration include sensor-guided control, solid model and knowledge representation, timing and scheduling of resources, and the design of robot controllers, power systems, and implementations.

2.2 Robot Configurations

A typical industrial robot is called the manipulator. Robot manipulators are composed of links connected by joints into an open chain kinematics as shown on Figure 2.1. Joints are usually either revolute type or prismatic type. The letter *R* represents Revolute joint, while the letter *P* represents prismatic joint. Figure 2.2 shows the symbolic representation of robot joints.

The number of joints dictates the degrees-of- freedoms (DOF) of the manipulator, where DOF relates to axes of movement of the arm and wrist or simply said as the number of joints. From Staubli Product Range (1998), the RX-90 Stäubli robot as seen in figure 2.3 has six revolute joints that makes it a six DOF robot. This robot is the model used in this study. The workspace or work envelope of the manipulator is the total volume swept out by the end-effector as the manipulator executes all possible motions. Figure 2.4 exhibits the workspace for RX-90, and table 2.1 lists its technical specifications.

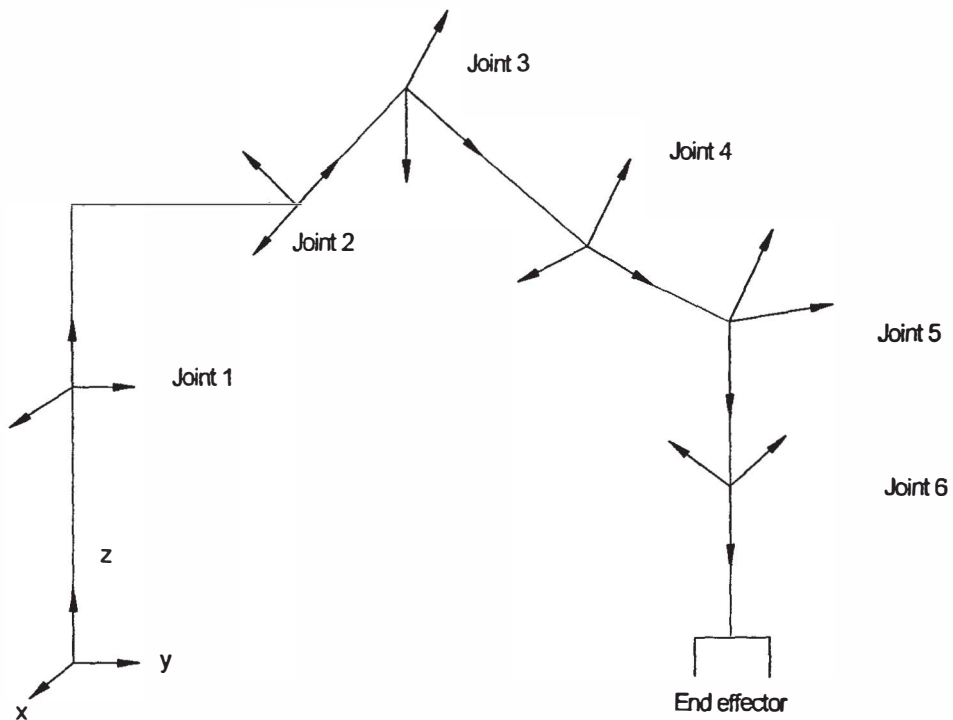


Figure 2.1: Open chain kinematics

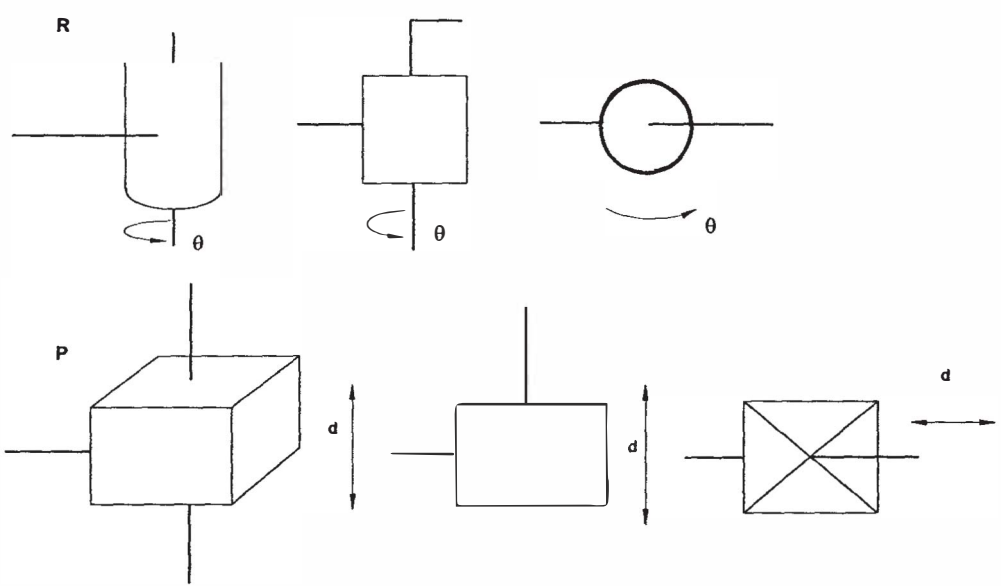


Figure 2.2: Symbolic representation of robot joint



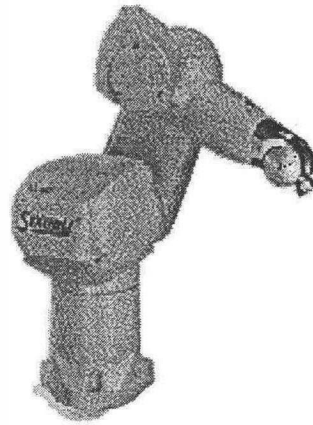


Figure 2.3: Staubli RX-90 robot (Staubli Product Range (1998))

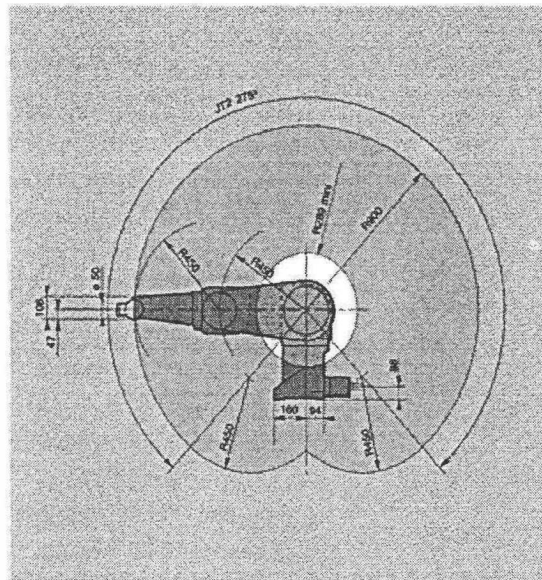


Figure 2.4: Staubli RX-90 robot workspace (Staubli Product Range (1998))

Table 2.1: RX-90 Technical Specifications

Reach at wrist	985 mm
Nominal load capacity	6 kg
Maximum load capacity	12 kg
Repeatability (ISO 9283)	± 0.02 mm
Degrees of freedom	6

2.3 Robot Arm Kinematics

Robot arm can be represented in several models of which all of these representations are in the form of mathematical equations or problems. Robot arm kinematics relates to the analytical study of the geometry of motion of a robot arm with respect to a fixed reference co-ordinate system without regard to the forces or moments that cause the motion. Some typically used robot arm representations are listed in the following:

- a) direct (forward) kinematics problem
- b) inverse kinematics problem
- c) Denavit-Hartenberg (DH) representation
- d) Lagrange-Euler formulation
- e) Newton-Euler formulation
- f) Generalised d'Alembert

Robot arms have two fundamental problems in term of arm kinematics, which are the forward kinematics and inverse kinematics. Forward kinematics problem is reduced to obtain the transformation matrix that relates the body-attached co-ordinate frame to the reference co-ordinate frame. Inverse kinematics problem can be solved by various methods such as inverse transform, screw algebra, dual matrices, dual quaternion, iterative and geometric approaches.

The DH representation proposed by Denavit and Hartenberg (1955) is a systematic approach of utilising matrix algebra to illustrate the spatial geometry of the robot links of the robot arm to a reference frame. The DH parameter is a tool to describe