ROBOT ARMS

Edited by **Satoru Goto**

INTECHWEB.ORG

Robot Arms
Edited by Satoru Goto

Published by InTech
Janeza Trdine 9, 51000 Rijeka, Croatia

Publishing Process Manager Sandra Bakic
Technical Editor Teodora Smiljanic
Cover Designer Martina Sirotic
Image Copyright sommthink, 2010. Used under license from Shutterstock.com

First published May, 2011
Printed in India

A free online edition of this book is available at www.intechopen.com
Additional hard copies can be obtained from orders@intechweb.org

Robot Arms, Edited by Satoru Goto
p. cm.
ISBN 978-953-307-160-2

Contents

Preface

Robot arms have been developing since 1960's, and those are widely used in industrial factories such as welding, painting, assembly, transportation, etc. Nowadays, the robot arms are indispensable for automation of factories. Moreover, applications of the robot arms are not limited to the industrial factory but expanded to living space or outer space. The robot arm is an integrated technology, and its technological elements are actuators, sensors, mechanism, control and system, etc.

Hot topics related to the robot arms are widely treated in this book such as model construction and control strategy of robot arms, robotic grasping and object handling, applications to sensing system and tele-sonography and human-robot interaction in a social setting.

I hope that the reader will be able to strengthen his/her research interests in robot arms by reading this book.

I would like to thank all the authors for their contribution and I am also grateful to the InTech staff for their support to complete this book.

Satoru Goto
Saga University
Japan

Part 1

Model and Control

1

Modeling Identification of the Nonlinear Robot Arm System Using MISO NARX Fuzzy Model and Genetic Algorithm

Ho Pham Huy Anh[1], Kyoung Kwan Ahn[2] and Nguyen Thanh Nam[3]
[1]*Ho Chi Minh City University of Technology, Ho Chi Minh City*
[2]*FPMI Lab, Ulsan University, S. Korea*
[3]*DCSELAB, Viet Nam National University*
Ho Chi Minh City (VNU-HCM)
Viet Nam

1. Introduction

The PAM robot arm is belonged to highly nonlinear systems where perfect knowledge of their parameters is unattainable by conventional modeling techniques because of the time-varying inertia, hysteresis and other joint friction model uncertainties. To guarantee a good tracking performance, robust-adaptive control approaches combining conventional methods with new learning techniques are required. Thanks to their universal approximation capabilities, neural networks provide the implementation tool for modeling the complex input-output relations of the multiple n DOF PAM robot arm dynamics being able to solve problems like variable-coupling complexity and state-dependency. During the last decade several neural network models and learning schemes have been applied to on-line learning of manipulator dynamics (Karakasoglu *et al*., 1993), (Katic *et al*., 1995). (Ahn and Anh, 2006a) have optimized successfully a pseudo-linear ARX model of the PAM robot arm using genetic algorithm. These authors in (Ahn and Anh, 2007) have identified the PAM manipulator based on recurrent neural networks. The drawback of all these results is considered the n-DOF robot arm as n independent decoupling joints. Consequently, all intrinsic coupling features of the n-DOF robot arm have not represented in its recurrent NN model respectively.

To overcome this disadvantage, in this study, a new approach of intelligent dynamic model, namely MISO NARX Fuzzy model, firstly utilized in simultaneous modeling and identification both joints of the prototype 2-axes pneumatic artificial muscle (PAM) robot arm system. This novel model concept is also applied to (Ahn and Anh, 2009) by authors.

The rest of chapter is organized as follows. Section 2 describes concisely the genetic algorithm for identifying the nonlinear NARX Fuzzy model. Section 3 is dedicated to the modeling and identification of the 2-axes PAM robot arm based on the MISO NAR Fuzzy model. Section 4 presents the experimental set-up configuration for MISO NARX Fuzzy model-based identification. The results from the MISO NARX Fuzzy model-based identification of the 2-axes PAM robot arm are presented in Section 5. Finally, in Section 6 a conclusion remark is made for this paper.

2. Genetic algorithm for NARX Fuzzy Model identification

The classic GA involves three basic operations: reproduction, crossover and mutation. As to derive a solution to a near optimal problem, GA creates a sequence of populations which corresponds to numerical values of a particular variable. Each population represents a potential solution of the problem in question. Selection is the process by which chromosomes in population containing better fitness value having greater probability of reproducing. In this paper, the roulette-wheel selection scheme is used. Through selection, chromosomes encoded with better fitness are chosen for recombination to yield off-springs for successive generations. Then natural evolution (including Crossover and Mutation) of the population will be continued until a desired termination or error criterion achieved. Resulting in a final generation contained of highly fitted chromosomes represent the optimal solution to the searching problems. Fig. 1 shows the procedure of conventional GA optimization.

It needs to tune following parameters before running the GA algorithm:

D: number of chromosomes chosen for mating as parents

N : number of chromosomes in each generation

L_t: number of generations tolerated for no improvement on the value of the fitness before MGA terminated

L_e: number of generations tolerated for no improvement on the value of the fitness before the extinction operator is applied. It need to pay attention that $L_e \langle\langle L_t$.

ρ : portion of chosen parents permitted to be survived into the next generation

q: percentage of chromosomes are survived according to their fitness values in the extinction strategy

The steps of MGA-based NARX Fuzzy model identification procedure are summarized as:

Step 1. Implement tuning parameters described as above. Encode estimated parameters into genes and chromosomes as a string of binary digits. Considering that parameters lie in several bounded region η_k

$$|w_k| \le \eta_k \text{ for } k=1,\dots,h. \tag{1}$$

The length of chromosome needed to encode w_k is based on η_k and the desired accuracy δ_k. Set i=k=m=0.

Step 2. Generate randomly the initial generation of N chromosomes. Set i=i+1.

Step 3. Decode the chromosomes then calculate the fitness value for every chromosome of population in the generation. Consider $F_{\max}^i$ the maximum fitness value in the i^{th} generation.

Step 4. Apply the Elitist strategies to guarantee the survival of the best chromosome in each generation. Then apply the *G-bit strategy* to this chromosome for improving the efficiency of MGA in local search.

Step 5.

1. *Reproduction:* In this paper, reproduction is set as a linear search through roulette wheel values weighted proportional to the fitness value of the individual chromosome. Each chromosome is reproduced with the probability of

$$\frac{F_j}{\sum_{j=1}^{N} F_j}$$

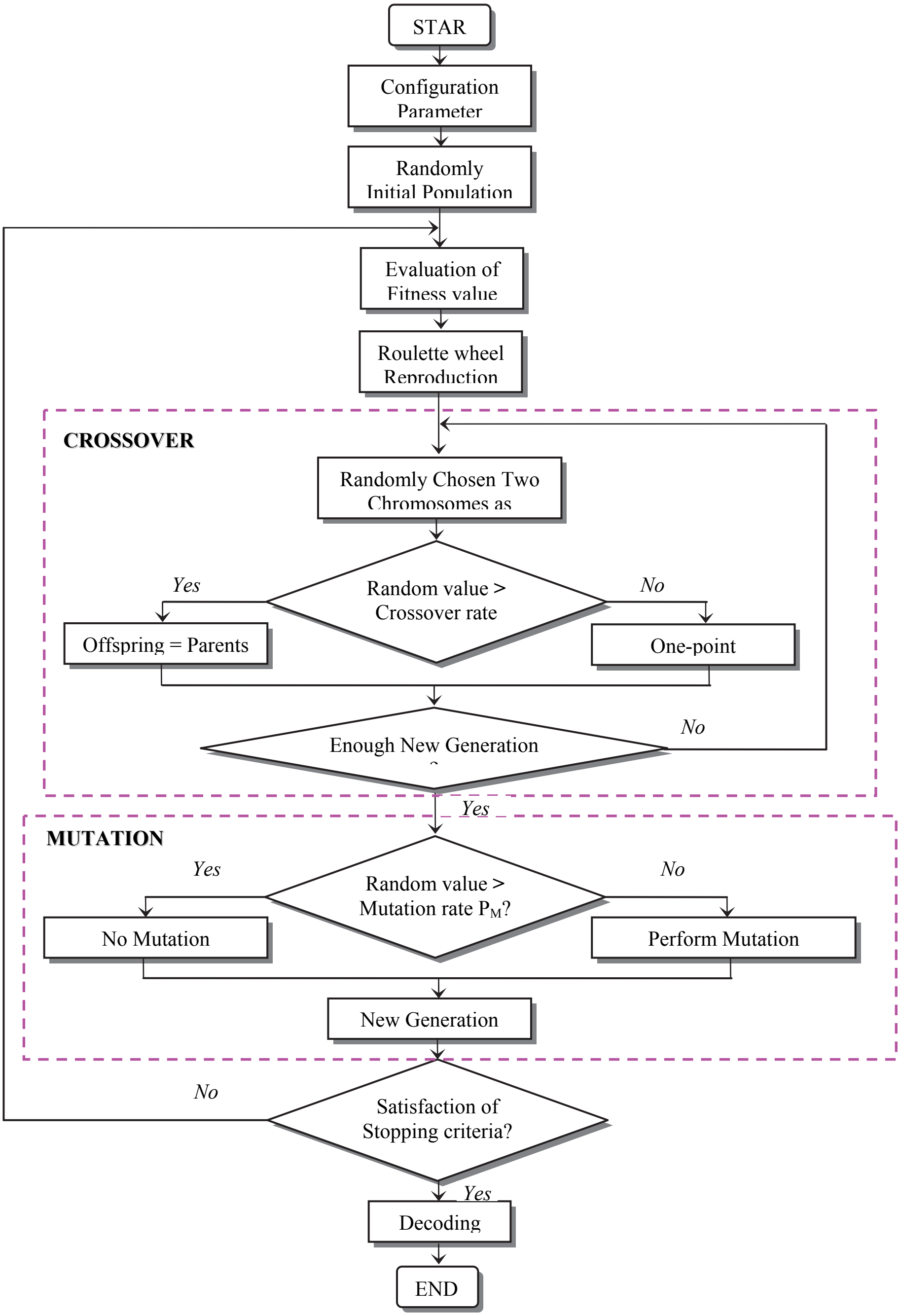

Fig. 1. The flow chart of conventional GA optimization procedure.

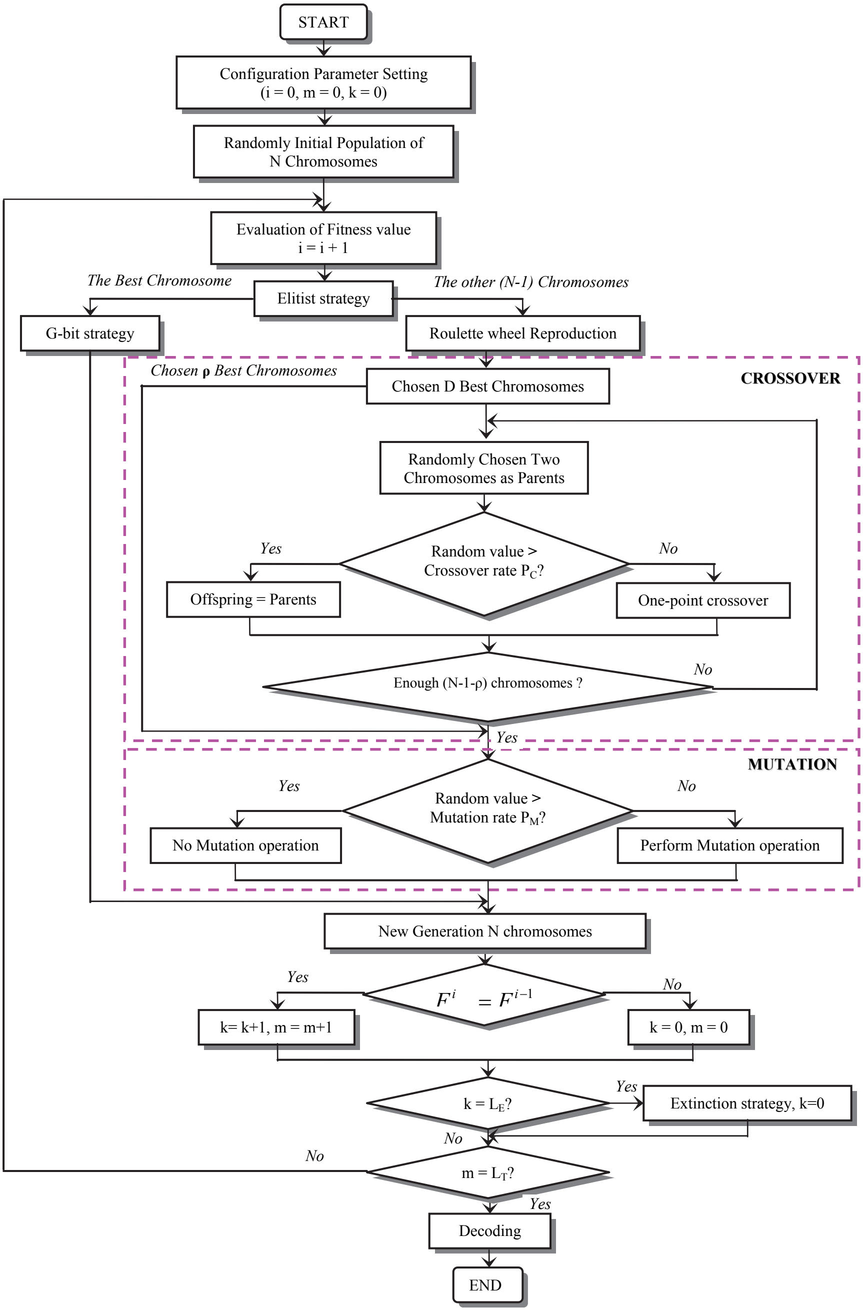

Fig. 2. The flow chart of the modified GA optimization procedure.

with j being the index of the chromosome ($j=1,\ldots,N$). Furthermore, in order to prevent some strings possess relatively high fitness values which would lead to premature parameter convergence, in practice, linear fitness scaling will be applied.

2. *Crossover:* Choose D chromosomes possessing maximum fitness value among N chromosomes of the present gene pool for mating and then some of them, called ρ best chromosomes, are allowed to survive into the next generation. The process of mating D parents with the crossover rate p_c will generate $(N-\rho)$ children. Pay attention that, in the identification process, it is focused the mating on parameter level rather than on chromosome level.
3. *Mutation:* Mutate a bit of string ($0 \leftrightarrow 1$) with the mutation rate P_m.

Step 6. Compare if $F_{\max}^{i} = F_{\max}^{i-1}$, then $k=k+1$, $m=m+1$; otherwise, $k=0$ *and* $m=0$.

Step 7. Compare if $k=L_e$, then apply the extinction strategy with $k=0$.

Step 8. Compare if $m=L_t$, then terminate the MGA algorithm; otherwise go to Step 3.

Fig. 2 shows the procedure of modified genetic algorithm (MGA) optimization.

3. Identification of the 2-Axes PAM robot arm based on MISO NARX fuzzy model

3.1 Assumptions and constraints

Firstly, it is assumed that symmetrical membership functions about the y-axis will provide a valid fuzzy model. A symmetrical rule-base is also assumed. Other constraints are also introduced to the design of the MISO NARX Fuzzy Model (MNFM).

- All universes of discourses are normalized to lie between –1 and 1 with scaling factors external to the DNFM used to give appropriate values to the input and output variables.
- It is assumed that the first and last membership functions have their apexes at –1 and 1 respectively. This can be justified by the fact that changing the external scaling would have similar effect to changing these positions.
- Only triangular membership functions are to be used.
- The number of fuzzy sets is constrained to be an odd integer greater than unity. In combination with the symmetry requirement, this means that the central membership function for all variables will have its apex at zero.
- The base vertices of membership functions are coincident with the apex of the adjacent membership functions. This ensures the value of any input variable is a member of at most two fuzzy sets, which is an intuitively sensible situation. It also ensures that when a variable’s membership of any set is certain, i.e. unity, it is a member of no other sets.

Using these constraints the design of the DNFM input and output membership functions can be described using two parameters which include the number of membership functions and the positioning of the triangle apexes.

3.2 Spacing parameter

The second parameter specifies how the centers are spaced out across the universe of discourse. A value of one indicates even spacing, while a value larger than unity indicates that the membership functions are closer together in the center of the range and more spaced out at the extremes as shown in Fig.3. The position of each center is