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Practice article

Control of a manipulator robot by neuro-fuzzy subsets form approach control optimized by the genetic algorithms

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A B S T R A C T

In this paper, we describe a new form of neuro-fuzzy-genetic controller design for nonlinear system derived from a manipulator robot. The proposed method combines fuzzy logic and neuronal networks which are of growing interest in robotics, the neuro-fuzzy controller does not require the knowledge of the robot parameters values. Furtheremore, the genetic algorithms (*GAs*) for complex motion planning of robots require an evaluation function which takes into account multiple factors. An optimizing algorithm based on the genetic algorithms is applied in order to provide the most adequate shape of the fuzzy subsets that are considered as an interpolation functions. The proposed approach provides a well learning of the manipulator robot dynamics whatever the assigned task. Simulation and practical results illustrate the effectiveness of the proposed strategy. The advantages of the proposed method and the possibilities of further improvements are discussed.

1. Introduction

Faced with the delicate problems of modeling and control of the complex systems such as the robots, the tools used are becoming increasingly cheaper and more powerful. The PID has proven its effectiveness in many problems of the industrial regulation. However, if the precision is required, it becomes inapplicable because of its linearity. In the recent decades, many research works have shown that the nonlinearities generate specific phenomena and these had to be taken into account to study the system satisfactorily. Indeed, either these phenomena are undesirable, and then the knowledge of their mechanisms is essential to avoid them, or they are inevitable and intrinsic for the system itself and then it becomes necessary to include, understand and model them, or it should be of well defined applications.

Therefore, one needs the introduction of other algorithms to develop new powerful controllers [1,2]. An approach having experienced significant developments these last years is the fuzzy controller relating to the systems containing knowledge: "IF (conditions) THEN (Action)" [41].

In spite of the significant number of applications developed by the fuzzy control, it always lacks tools that make it possible to analyze these controllers [34,39].

To avoid the problem of the expertise, the researchers tried to replace the expert by several methods such as the neural networks and the genetic algorithms. Neural networks which are based on the mechanisms of operations of the human brain, in the form of layers [35,37,38].

The genetic algorithms are also very much used for the optimization of fuzzy regulators. They are based on the theory of evaluation of the most adapted elements of a generation towards the other, so that the best adapted ones would last in time, while the other should disappear.

The proposed adaptive neuro-fuzzy optimized by *GAs* control scheme has some advantages over classical fuzzy control and neural networks control schemes [3,4]. For example, in a classical fuzzy controller design, certain controller parameters must be tuned by trial and error. Such parameters include scalars (or gains) for its inputs and outputs data, the number of membership functions, the width of a single membership function, and the number of control rules [42–51].

On the contrary, the adaptive neuro-fuzzy controller based on the dynamic model estimation would allow the parameters to be tuned automatically [36]. In addition, the performance of the neuro-fuzzy controller optimized by *GAs* is also considered to be excellent.

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The neuro-fuzzy-genetic controller does not require knowledge of the robot's parameters values. It needs, neither system dynamic model nor control experts for the robot control problem.

The application of neuro-fuzzy to manipulator robot has motivated considerable research in this area in recent years. In Ref [5], an adaptive control using multiple incremental fuzzy neural networks (*FNNs*) was presented. The controller is combined by a feedback controller and several *FNNs* to learn inverse dynamics of the manipulator robot for different tasks. The several *FNNs* are obtained dynamically using an incremental hyper-plane-based fuzzy clustering algorithm to compensate the unknown disturbances of the system. In Ref. [6], a decentralized intelligent control method for a robust control of underwater manipulator was developed. The controller is based on a neuro-fuzzy approach where the feedback gains are adapted using fuzzy logic, whereas a neural networks is used to add to the controller a feed-forward compensation input. The neural network is trained using the back-propagation approach to estimate the system dynamics from the inputs-outputs data. Therefore, the proposed method does not depend on modeling and dynamics estimation system. The same authors in Ref. [7] proposed an intelligent controller used a neuro-fuzzy approach for precise control, robust and energy efficient. The decentralized controller is a PD type, with fuzzy setting feedback gains modified using modified fuzzy membership functions. The magnitude of the gains and thus, the energy expenditure is reduced by the neural network based on the identification of the system dynamics and hydrodynamic disturbances. In Ref. [8], a comparative study of several hybrid neuro-fuzzy adaptive control systems for control of six degrees of freedom (Puma 560) robot arm, with uncertainties were presented. The proposed controller combines ANFIS based controllers, with some well established traditional controllers (computed torque control, feed forward inverse dynamics, and critical damping inverse dynamics control).

In Ref. [9], such orthogonalization and passivity properties are taken into account to design a neuro-fuzzy system (NFS) like a PID controller to ensure tracking by exploring a new energy re-shaping of the closed loop system through a self-optimization of the dissipation rate gain (DRG) without any knowledge of the robot dynamics. In Ref. [10], Fuzzy Logic System (FLS) was presented to generate rules using neuro-fuzzy methods. In Ref. [11], a single hidden layer in a fuzzy recurrent wavelet neural network (SLFRWNN) was developed and used for the function approximation and the identification of dynamic systems. And In Ref. [12], a supervised training algorithm based on sliding mode theory that implements fuzzy reasoning on a spiking neural networks, for the trajectory control problem of a robotic manipulator was developed and tested. In Ref. [32], a new neuro-fuzzy classifier which draws its inspirations from the concepts of the linguistic hedges was used.

To well learn dynamics of the manipulator robot, which represent an extension of the idea given by Refs. [7,32] where they used a triangular membership functions (MFs), with linguistic hedges to modify the shape of the MFs, in this work, we used a neuro-fuzzy-genetic controller. The neural networks are proposed for the automatic extraction of the fuzzy rules, using a Kalman filter as a training means. To optimize the site of the fuzzy subsets, we used the *GAs*, and since there are several forms of the fuzzy subsets such as triangular, Gaussian, etc …, and as a contribution, we used an interpolation function with three points, and then with five points, for each fuzzy subset, and we optimized the curves by the *GAs*, to find the most suitable shape of a fuzzy subset, which is going to be adapted according to the load.

Organization of the paper is as follows first, a brief introduction to robotics. Section 2 introduces the dynamic model of a manipulator robot. This is followed by Section 3 which describes in detail the *GAs*. In Section 4, the neuro-fuzzy control is presented. Section 5 present the Neuro-Fuzzy Subsets Form-Genetic Control (N-FSF-GC). The simulation and practice results with discussions are given in Section 6. Finally, Section 7 concludes the paper.

2. The manipulator robot ROBAI Cyton Gamma 1500

The ROBAI Cyton Gamma 1500 is a humanoid robot arms, with seven degrees of freedom. It can reach around obstacles and by pass-gaps, reconfigure for strength, and manipulate objects with a clever fluid movement. In our study we only keep the first three joints with the end effector Fig. 1. The three degrees of freedom are controlled by three DC servo motors, dynamixel MX-64.

2.1. Dynamic model of the robot

A manipulator robot is essentially a positioning device. In order to control the position we must know the dynamic properties of the manipulator to size the force that must be exerted to drive it: an insufficient force implies that the manipulator is too slow to react. Too much force can get the robot collide with the external objects or oscillate around the desired position.

Deriving the motion dynamic equations for robots is not an easy task because of the large number of degrees of freedom and non-linearities of the system [33]. The dynamic model of the robot includes dynamic actuators that produce the torques to control the robot and dynamics of the chain that transmit power to the actuator links given by (1).

We will model the robot with only the second and the third revolute joints (Fig. 1).

The most general form is [40].

$$M(q)\ddot{q} + H(q,\dot{q}) + G(q) + F(q,\dot{q}) = \tau \tag{1}$$

Where: $M(q)$ 2×2 inertia matrix.

$H(q,\dot{q})$ 2×1 Coriolis/centrifugal vector.
$G(q)$ 2×1 gravity vector.
$F(q,\dot{q})$ 2×1 friction torque.
$q,\ \dot{q},\ \ddot{q}$ 2×1 position, vilocity and accelerations vector.
τ 2×1 the generalized joint torque vector.

2.2. Trajectory generation

The robot dynamics require from us to impose realizable trajectories. Continuity in position, speed and acceleration makes it possible for the robot to continue the trajectory with realizable controls Fig. 4.

Fig. 1. The ROBAI Cyton arm.