Proceedings of the 8th IEEE Mediterranean Conference
on Control and Automation (MED 2000)
Rio, Patras, GREECE 17-19 July, 2000

THE GENETIC-CONNECTIONIST ALGORITHM FOR COMPLIANT ROBOTIC TASKS

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Abstract. In this paper, a systematic connectionist controller design approach is proposed to guarantee stability and desired performance of the robotic system for compliant tasks by effectively combining genetic algorithms(GA) with neural classification and neural learning control techniques. The effectiveness of the approach is shown by using a simple and efficient decimal and binary GA optimization procedures to tune and optimize the performance of a neural classifier and controller, together with tuning of feedback controller.In order to demonstrate the effectiveness of the proposed GA approach, some compliant motion simulation experiments with robotic arm placed in contact with dynamic environment have been performed.

Keywords. Genetic algorithms, Neural networks, Learning Control, Robotics.

1. INTRODUCTION

The one of the most delicate problems in compliant motion control of robots interacting with the dynamic environment is the stability of both desired motion and interaction forces. It is well known, that beside uncertainties of robot dynamic model, environment uncertainties also can have a strong influence on the quality of robot performance.A multitude of various control approaches , point to the stability of control task as a problem which is not yet satisfactorily solved, both from the theoretical and the practical standpoint. Without knowing a sufficiently accurate environment model it is not possible to determine, for instance, nominal (desired) contact force. One excellent possible solution is to use enhanced learning concept for contact tasks. The second important characteristic of contact tasks is their repetitive nature which is very important for process of learning by trial-and-error procedure. As solution for the expressed problem, some researchers [5], [2],[3] used the intelligent techniques for dynamic environment identification.

In this paper, a main idea is to enhance capabilities of proposed connectionist control algorithm for contact robot tasks [3], synthesizing the new control algorithms based on genetic tuning of non-learning control part (conventional force PI controller) and learning control part (neural "off-line" classifier and neural "on-line" controller). The are few efficient proposed GA methods with application for different special purposes in robotics [1], [4]. We hereby proposed a systematic approach to controller design approach for both closed-loop stability and desired performance by using GA's to tune the position and force feedback gains. The GA utilized is selected to be of the decimal real number type to achieve simple and efficient computational process. Two type of fitness functions are considered for optimization of the controller performance: integral of squared errors (ISE) and integral time-multiplied absolute value of errors (ITAE).

The main feature of proposed learning control part is integration of two multilayer perceptrons with previously mentioned control laws based on the stabilization of the interaction force [3]). The first proposed neural network plays the role of a robust on-line learning controller needed to compensate uncertainties of the dynamic model of manipulation robots in contact with dynamic environment. The second neural network performs the classification of unknown parameters and structure of environment. In order to improve convergence process, efficient GA is proposed in order to choose the appropriate topology of the proposed multi layer perceptron that performs neural classification. Also, in order to improve the learning process, GA optimization is used for determination of weighting factors for the neural compensation of robot dynamic model in on-line control algorithm.

2. BASIC NEURAL CONTROL LAW

2.1 Synthesis of Nonlearning Control Law

The dynamic model of the robot interacting with the environment is described by a vector differential equation in the form:

$$H(q)\ddot{q} + h(q,\dot{q}) + J^T(q)F = \tau \qquad (1)$$

where, $q = q(t)\epsilon R^n$ are robot generalized coordinates; $H(q)\epsilon R^{n\times n}$ is inertia matrix of the manipulation mechanism; $h(q,\dot{q})\epsilon R^n$ is nonlinear function of centrifugal, Coriolis and gravitational moments; $\tau = \tau(t)\epsilon R^n$ is input control vector; $J^T(q)\epsilon R^{n\times m}$ is Jacobian matrix; $F = F(t)\epsilon R^m$ is vector of generalized forces and moments. In the frame of robot joint coordinates, the model of environment dynamics can be presented in the form:

$$M(q)\ddot{q} + L(q,\dot{q}) = S^T(q)F \qquad (2)$$

where $M(q)\epsilon R^{n\times n}$ is a nonsingular matrix; $L(q,\dot{q})$ ϵR^n is a nonlinear vector function; $S^T(q)\epsilon R^{n\times n}$ is the matrix with $rank(S) = n$.In practice it is more appropriate to adopt the relationship defined by specification of the target impedance:

$$F = M'\Delta\ddot{x} + B'\Delta\dot{x} + K'\Delta x \qquad (3)$$

where

$$\Delta x = x - x_0 \qquad (4)$$

where $x_0\epsilon R^n$ denotes the coordinate vector in Cartesian coordinates of the point of contact between the end-effector (tool) and a constraint surface. The matrices M', B', K' define the target impedance which can be selected to correspond to various objectives of the given manipulation task.

In the case of contact with the environment, the robot control task can be described as robot motion along a programmed trajectory $q_p(t)$, when a desired force of interaction $F_p(t)$ acts between the robot and the environment. These two functions must satisfy the following relation:

$$F_p(t) \equiv f(q_p(t), \dot{q}_p(t), \ddot{q}_p(t)) \qquad (5)$$

The control algorithm based on stabilization of the interaction force with a preset quality of transient responses is considered, which has the following form [6]:

$$\tau{=}H(q)M^{-1}(q)[-L(q,\dot{q}) + S^T(q)F] + h(q,\dot{q}) + J^T(q)\{F_p - \int_{t_0}^{t}[KFP\mu(\omega){+}KFI\int_{t_0}^{t}\mu(\omega)dt]d\omega\} \qquad (6)$$

where $\mu(t){=}F(t) - F_p(t)$;$KFP\epsilon R^{n\times n}$ - is the diagonal matrix of proportional force feedback gains; $KFI\epsilon R^{n\times n}$ - is the diagonal matrix of integral force feedback gains. Here , it has been assumed that the interaction force in transient process should behave according to the following differential equation:

$$\dot{\mu}(t) = Q(\mu) \qquad (7)$$

$$Q(\mu) = -KFP\mu - KFI\int_{t_0}^{t}\mu dt \qquad (8)$$

In this case, environment dynamics model has explicit influence on the performance of contact control algorithm, also having influence on PI force local gains. It is clear that without knowing a sufficiently accurate environment model it is not possible to determine the nominal contact force $F_p(t)$. Beside that, inexact model of environment dynamics can significantly influence the contact task performances. Hence, in our analysis, if the aim is to obtain the same quality of force steady-state processes for different environments , the same force performances can be achieved only by parameter identification of robot environment models, and with equal fixed PI force local gains.

2.2 The Comprehensive Neural Control Law

The control algorithm presented in the previous subsection does not work in a satisfactory way if there is no sufficiently accurate information about the type of robot environment and the parameters of their models. Hence, in order to enhance connectionist learning of general robot-environment model, new method is proposed which main idea is using comprehensive neural network approach through off-line learning process and on-line sufficiently exact classification of robot dynamic environment together with learning of dynamic robot uncertainties. The first objective in application of the learning compliance control algorithm is the learning of robot dynamic model and compensation of robot model uncertainties. For this purpose, the multilayer perceptron is used as a part of non-learning control strategies mentioned before. In this case, "hybrid" approach based on the multilayer perceptron and a priori known model with imprecise values of matrix $\hat{H}(q)$ and vector $\hat{h}(q,\dot{q})$ is used in the synthesis of learning control law. In order to achieve good tracking performance with the presence of model uncertainties, multilayer perceptron is integrated into non-learning control law with desired quality of transient process for interaction force:

$$P^{NN} = F_1(w_{jk}^{NNab}, q_p, \dot{q_p}, \ddot{q_p}, q, \dot{q}) \qquad (9)$$

$$\tau = \hat{H}(q)\hat{M}^{-1}(q)[-\hat{L}(q,\dot{q})+\hat{S}^T(q)F]+h(q,\dot{q})+ J^T(q)\{F_p - \int_{t_0}^{t}[KFP\mu(\omega)+KFI\int_{t_0}^{t}\mu(\omega)dt]d\omega\} +P^{NN} \quad (10)$$

where F_1 is a nonlinear mapping for the perceptron NN ; P^{NN} is a compensation part of the learning control law; w_{jk} are weighting factors for perceptron NN.

The neural network classifier based on four-layer perceptron is chosen for the purpose of classification due to good generalization properties. Its objective is to classify parameters of environment in an on-line manner. Hence, application of connectionist approach to this type of problems is divided into two phases: first, related to the acquisition process and off-line training of proposed neural network and, second, association phase, where on-line learning control algorithms based on excellent generalization properties of neural networks must assure the necessary quality of the system performances.

2.3 Acquisition Process of Neural Classifier - the First Phase

In the acquisition process of the first phase, based on the real-time realization of proposed contact control algorithm and using a previously chosen set of different working environments, force data from force sensors are collected. In the case of the compliance control algorithm with stabilizing interaction force, for each chosen robot environment and for the chosen contact control algorithm, values of normal force $F_n(t)$ and error of normal force ($\Delta F_n = F_n - F_{np}$, where F_{np} is desired normal force) in time instants $(t),(t-1),(t-2)$ and $(t-3)$ are measured, calculated, and stored as special input patterns for training of neural network. On the other side, the acquisition process must be accomplished using various robot environments, starting with the environment with a low level of system characteristic (for example, with a low level of environment stiffness) and ending with the environment with a high level of system characteristic (with high level of environment stiffness).

After that, during the extensive off-line training process, neural network receives a set of input-output patterns, where input variables form a previously collected set of force data. As desired output, neural network has a value between zero and unity which exactly defines the type of training robot environment. In our example, training of neural network is accomplished with 5 different working environment. The input variables and target outputs for neural classifier are shown in Table 1.

Table 1. Inputs and target outputs of neural classifier

Input data for classifier	Classifier outputs
$F_n(t)$	Styrofoam 0.00
$\Delta F_n(t)$	Silicon 0.25
$\Delta F_n(t-1)$	Rubber 0.50
$\Delta F_n(t-2)$	Plastic 0.75
$\Delta F_n(t-3)$	Steel 1.00

2.4 On-Line Compliance Control Algorithm - The Second Phase

For the control algorithm based on stabilization of the interaction force with a preset quality of transient process, the general impedance model of robot environment (3) is chosen. Hence , after the off-line training process , on-line version of compliance control algorithm with neural classifier with fixed weighting factors based on on-line force and force errors inputs is given by the following relations for specified environment model (3):

$$\tau = -H(q)\hat{M'}^{-1}(q)[\hat{B}'\dot{q} + \hat{K}'q] + h(q,\dot{q}) + (J^T(q) - H(q)\hat{M'}^{-1})\{F_p - \int_{t_0}^{t}[KFP\mu(\omega) + KFI\int_{t_0}^{t}\mu(\omega)dt]d\omega\} \quad (11)$$

$$\hat{M}' = f_{M'}(y), \quad \hat{B}' = f_{B'}(y), \quad \hat{K}' = f_{K'}(y) \quad (12)$$

where $f_{M'}, f_{B'}, f_{K'}$ are linear interpolation functions for parameters of matrices M', B', K';

According to the similar principle, the same condition for control law and all different robot environments is using the same local PI force gains. In our case, parameters of dynamic models of different chosen environments M', B', K' are stored as an information necessary for calculating the basic control algorithm. In the case of the unknown environment, information from neural classifier output can be efficiently utilized for calculation of necessary environment parameters M', B', K' by linear interpolation procedures.

3. GA OPTIMIZATION

3.1 GA Tuning of PI Force Feedback Gains

In order to further simplification of genetic process, the set of tuning force gains KFP and KFI is reduce to single parameter ω_n, where ω_n is the natural frequency of the second order linear system defined by characteristic equations:

$$\mu_i(\omega)+\int_{\omega_0}^{\omega}[KFP_{ii}\mu_i(\omega)+KFI_{ii}\int_{t_0}^{t}\mu_i(\omega)dt]d\omega=0 \tag{13}$$

Previous forms of characteristic equations are equivalent to the following equation:

$$\ddot{\eta}_i + 2\zeta\omega_n\dot{\eta}_i + \omega_n^2 = 0 \tag{14}$$

If we assume for second-order system that critical damping ($\zeta = 1$), feedback gains are given by

$$KFP_{ii} = 2\omega_n, \qquad KFI_{ii} = \omega_n^2 \tag{15}$$

On this way, only natural frequency is chosen for genetic tuning. The initial population of size N is generated randomly to start the optimization process. The total population of each generation is evaluated using suitable chosen performance criterion (ISE or ITAE). Reproduction as primary genetic operator is based on using the best $N/2$ individuals of the current generation to be parents for generating the next generation. Weighted-average cross-over genetic operator based on decimal numbers is applied [4]. From parents ω_{n1} and ω_{n2}, two new offsprings are reproduced by the following terms:

$$\omega_n^1 = r * \omega_{n1} + (1-r) * \omega_{n2} \tag{16}$$

$$\omega_n^2 = (1-r) * \omega_{n1} + r * \omega_{n2} \tag{17}$$

where $r\epsilon(0,1)$ is a random number. Mutation are based on the following changes of natural frequency:

$$\omega_n^1 = \omega_n + (r-0.5) * 2 * \Delta\omega_n^{max} \tag{18}$$

where $\Delta\omega_n^{max}$ is the maximum change of natural frequency. The objective of the GA optimization is to obtain better end-effector performance, i.e. to find PI force feedback gains as fast as possible with minimal oscillation and overshoot. The fitness functions are defined according to following equations:

$$ISE = \int_0^T \mu^2(t)dt \quad ITAE = \int_0^T \mid t\mu^2(t) \mid dt \tag{19}$$

3.2 Improvement of Learning Process for Neural Classifier by GA Approach

One of the main design parameters related to network topology is the number of neurons on each hidden layer. In order to avoid heuristic selection of number of neurons based on long-time simulation experiments, a new approach to network topology selection based on genetic algorithm. First step in application of genetic algorithms is to set a generation of initial population of possible network topologies in a random way. In this case, it is a previously determined number of pairs which define the number of neurons in the first and the second hidden layer. For the second step, it is necessary to convert the numeric values of number of neurons in hidden layers to a binary representation (two 8-bit strings). The crucial point in GA algorithm is the choice of fitness function. Our aim is to choose a topology of neural network with the minimum approximation error, i.e. we can use the value of well-known mean square error criterion at the end of previously defined learning epoch as a quality information for search :

$$E^p(k) = 0.5\sum_{i=1}^{k} \mid \hat{y}^p(k) - y^p(k) \mid^2 \tag{20}$$

where $\hat{y}^p(k)$ is the target output of neural network in learning epoch k; $y^p(k)$ is the real value of network output in learning epoch k; $E^p(k)$ is the value of mean square criterion for one input-output pattern p ($p \in P$) in learning epoch k; P is the set of input-output pairs. Now, after neural network training, all strings in initial population have their own fitness function. There are many selection procedures, but in this case the roulette wheel selection that chooses individuals for reproduction according to their fitness function values is chosen . Due to the experience in training of multilayer perceptrons, one limitation in selection procedure is included, i.e. only pairs of strings where number of neurons in the first hidden layer is greater than the number of neurons in the second hidden layer are ready for reproduction purposes. In order to improve the search process, the following two genetic operators (*crossover* and *mutation*) are applied with some limitations. *Uniform crossover* , which swaps each column in chromosome representation having the same probability is chosen. In order to avoid great changes in numerical representation of the proposed problem and the proper nature of the search problem, the second operator mutation is limited only to five lower bits of each string. Now the complete new population is generated, which is converted into numerical representation after decoding process , and which is ready for evaluation of its fitness function through neural network training process with a new network topology. The process is stopped when the desired value of fitness function is achieved. In similar way, GA solution based on binary representation is applied for determination of weights of the second neural network for compensation of robot uncertainties.

4. SIMULATION EXPERIMENTS

For demonstrating the performance of contact control schemes with GA tuning of general controller and neural elements, compliance control implementations are simulated using robot MANUTEC r3 in contact with various models of robot environment. Complete parameters of robotic system and robotic task are given in [3].To investigate the effect of GA optimization procedure for tuning of PI local force gains, simulation experiments were conducted with initial appropriate set of PI local force gains. It is necessary to specify range of controller parameter(natural frequency). Including the maximal torque value given by actuator limits, we obtain the range of the natural frequency ($0 < \omega_n \leq 32$).

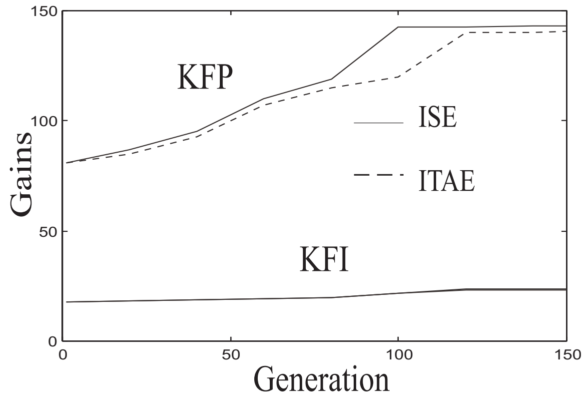

Fig. 1. Best force feedback gains KFP and KFI according to ISE and ITAE criterions

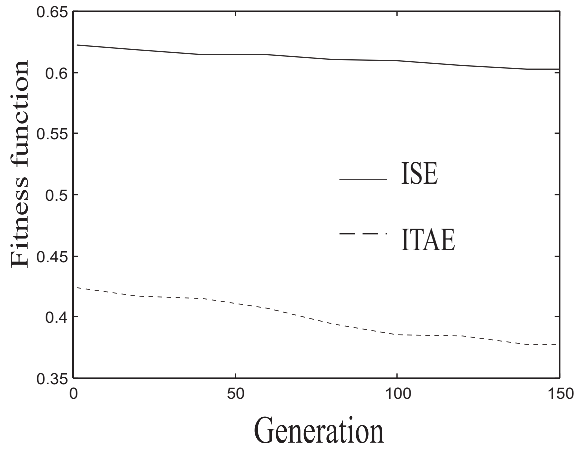

Fig. 2. Best values of ISE and ITAE criterion during evaluation process

In the simulation, the population size of each generation is set to be N=40. The maximum mutation values for $\Delta\omega_n^{max} = 0.5$ The evaluation process is terminated when the change of fitness function is small in a certain number of successive generations. The results of GA optimization procedure are shown on the Fig. 1 and 2.It is obvious that better performance (corresponding to smaller values of the fitness functions) will be obtained with the progression of GA process. Based on previous GA optimization, PI force gains are synthesized using the same system frequencies for all different working environments ($\omega_n = 11.86Hz.$). In the phase of connectionist off-line training, the efficient genetic algorithm is used in order to select the optimal topology of neural network. The initial population of 8 pairs of possible topology solutions is given and 3 successive generations are simulated. The following genetic parameters are chosen: crossover probability $pcros = 0.3$ and mutation probability $pmut = 0.03$. As example, the whole evaluation process is shown in the table 2. Using this procedure, the following optimal network topology is selected: 6-50-20-1 (50 neurons in first hidden layer, 20 neurons in second hidden layer). The results in table show the betterment process of fitness function, i.e. convergence to optimal solution for number of neurons in hidden layers. Using GA adopted network topology and the learning process, training process is achieved with stored weighting factors. In the generalization test, the "off-line learned" and GA tuned neural classifier is included in control algorithm for the recognition of unknown robot environment. The second neural network also tuned by GA for uncertainty compensation use the same learning rules and parameters as in the case of off-line neural network. The profile model of environment using general impedance model with additional stiffness members is adopted. In this case, the robot environment with dominant stiffness $K'_{22} = 50000$ N/m is selected. The neural classifier based on input force data generates output of network which defines the other necessary parameters of the control law. For comparison, the example of application of learning control laws with and without exact information of environment stiffness are given in Fig. 3. It is clear that in the case when there are no exact information about robot environment, the quality of performance is poor.

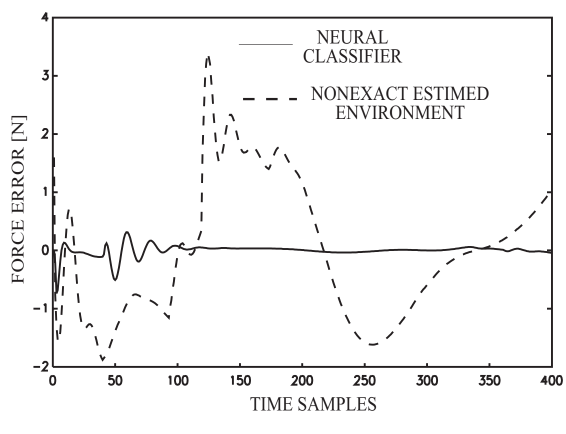

Fig. 3. Force error - comparison with and without neural classifier

Table 2. GA evaluation process for topology of neural classifier

INIT.POPUL.								
N0.	PAIR	HROM.-PAR.	F.FUN.-PAR.	DIST.				
1	12-15	0000110000001111	0.412	0.112				
2	18-17	0001001000010001	0.403	0.110				
3	16-20	0001000000010100	0.484	0.132				
4	26-28	0001101000011100	0.460	0.126				
5	25-16	0001100100010000	0.480	0.131				
6	13-11	0000110100001011	0.497	0.136				
7	12-24	0000110000011000	0.439	0.120				
8	28-28	0000111000011100	0.478	0.130				
MinFF=0.403	MaxFF=0.497	AveFF=0.456	SumFF=3.655					
GENER.N0.1								
N0.	PAIR	HROM.-CHI.	F.FUN.-CHI.					
1	56-28	0011100000011100	0.489					
2	16-20	0001000000010100	0.484					
3	29-16	0001110100010000	0.384					
4	25-16	0001100100010000	0.480					
5	13-11	0000110100001011	0.497					
6	13-11	0000110100001011	0.497					
7	25-16	0001100100010000	0.480					
8	28-28	0001110000011100	0.478					
EXP.SELECT. SELECTION	0.901 0.883	1.059 1.008 43856648	1.050 1.089	0.960 1.046				
N0.OF CROSS.	15		NO.OF MUTAT.	2				
MinFF=0.384	MaxFF=0.497	AveFF=0.473	SumFF=3.791					
GENER.NO.2								
N0.	PAIR	HROM.-CHI.	F.FUN.-CHI.					
1	50-20	0011001000010100	0.497					
2	16-20	0001000000010100	0.484					
3	25-8	0001100100001000	0.456					
4	13-11	0000110100001011	0.497					
5	13-11	0000110100001011	0.497					
6	13-11	0000110100001011	0.497					
7	16-20	0001000000010100	0.484					
8	16-20	0001000000010100	0.484					
EXP.SELECT. SELECTION	1.032 1.021	0.810 1.012 21756627	1.050 1.050	1.012 1.008				
N0.OF CROSS.	15		NO.OF MUTAT.	2				
MinFF=0.456	MaxFF=0.497	AveFF=0.487	SumFF=3.900					

5. CONCLUSIONS

This paper presents a new GA approach for robot learning compliance control in order to guarantee stability and desired performance of the robotic system. Some efficient genetic algorithms with binary and decimal representation are applied for optimization of the performance of a neural classifier and controller, together with tuning of non-learning feedback controller. The simulation results demonstrate the effectiveness of the proposed new GA-neural control approach.

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