A HIERARCHICAL FUZZY-NEURAL MULTI-MODEL
An application for a mechanical system with friccion identification and control

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Abstract: A Recurrent Trainable Neural Network (RTNN) with a two layer canonical architecture and a dynamic Backpropagation learning method are applied for identification and control of complex nonlinear mechanical plants. The paper uses a Fuzzy-Neural Hierarchical Multi-Model (FNHMM), which merge the fuzzy model flexibility with the learning abilities of the RNNs. The paper proposed the application of two control schemes, which are: a trajectory tracking control by an inverse FNHMM and a direct adaptive control, using the states issued by the identification FNHMM. The proposed control methods are applied for a mechanical plant with friction system control, where the obtained comparative results show that the control using FNHMM outperforms the fuzzy and the neural single control.

1 INTRODUCTION

Recent advances in understanding of the working principles of artificial neural networks has given a tremendous boost to identification and control tools of nonlinear systems, (Narendra and Parthasarathy, 1990; Hunt et al., 1992; 1995, Miller et al., 1992; Omatu et al., 1995). Most of the current applications rely on the classical NARMA approach, where a feedforward network is used to synthesize the nonlinear map, (Narendra and Parthasarathy, 1990; Hunt et al., 1992). This approach has some disadvantages, (Hunt et al., 1992), like that: the network inputs are a number of past system inputs and outputs, so to find out the optimum number of past values, a trial and error must be carried on; the model is naturally formulated in discrete time with fixed sampling period, so if the sampling period is changed the network, must be trained again; problems associated with stability, convergence and rate of convergence of this networks are not clearly understood and there is not a framework available for its analysis in vector-matricial form, (Gupta et al., 1994; Jin and Gupta, 1999); it is a necessary condition, that the plant order has to be known. Besides to avoid these difficulties, a new Recurrent Neural Networks (RNN) topology, and a Backpropagation (BP) like learning algorithm, (Baruch *et al.*, 2001a, 2002), has been designed. This RNN model is a parametric one, permitting the use of the obtained parameters during the learning for control systems design. Furthermore, the designed RNN model is a system state predictor/estimator, which permits to use the obtained system states directly for state-space control. The designed RNN model has the advantage to be completely parallel, so its dynamics depends only on the previous step and not on the other past steps, determined by the systems order which simplifies the computational complexity of the learning algorithm with respect to the sequential RNN model of (Frasconi, Gori and Soda, 1992).

For complex nonlinear plants, the authors of (Baruch *et al.*, 1998, 2001b) proposed to use a fuzzy-neural multi-model, which is applied for systems with friction identification and control. This model explore the ideas of (Takagi and Sugeno, 1985), using in the right hand side of the fuzzy rules static or dynamic functions (see Babushka and

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Verbruggen, 1997), the multiple neural approach (see Eikens and Karim, 1999), and further a recurrent neural network multi-models (see Baruch, *et al.*, 1998; Mastorocostas and Theocharis, 2002). The difference between the used in (Mastorocostas and Theocharis, 2002) fuzzy neural model and the approach of (Baruch, *et al.*, 1998), is that the first one uses the (Frasconi, Gori and Soda, 1992) FGS-RNN model, which is sequential one, and the second one uses the Recurrent Trainable NN (RTNN) model (Baruch *et al.*, 2001a, 2002), which is completely parallel one.

2 MODELS DESCRIPTION

2.1 Recurrent Neural Model and Learning

The RTNN model is described by the following equations, (see Baruch *et al.*, 2001a, 2002):

$$X(k+1) = JX(k)+BU(k) \quad (1)$$

$$Z(k)=S[X(k)] \quad (2)$$

$$Y(k) = S[CZ(k)] \quad (3)$$

$$J = \text{block-diag}\ (Ji);\ |Ji| < 1 \quad (4)$$

Where: X(k) is a N - state vector; U(k) is a M- input vector; Y(k) is a L- output vector; Z(k) is a L- auxiliary vector; S(x) is a vector-valued activation function with compatible dimension; J is a weight-state diagonal matrix with elements J_i ; the equation (4) is a stability condition, imposed on the weights J_i; B and C are weight input and output matrices with compatible dimensions and block structure, corresponding to the block structure of J. As it can be seen, the given RTNN model is a completely parallel parametric one, with parameters - the weight matrices J, B, C, and the state vector X(k). The controllability, observability and stability of this model are considered in (Baruch *et al.*, 2002). The general BP learning algorithm is given as:

$$W_{ij}(k+1) = W_{ij}(k) +\eta\ \Delta W_{ij}(k) +\alpha\ \Delta W_{ij}(k-1) \quad (5)$$

Where: W_{ij} (C, J, B) is the ij-th weight element of each weight matrix (C, J, B) of the RTNN model to be updated; ΔW_{ij} is the weight correction of W_{ij}; η, α are learning rate parameters. The weight updates ΔC_{ij} , ΔJ_{ij}, ΔB_{ij} of C_{ij}, J_{ij}, B_{ij} are:

$$\Delta C_{ij}(k) = [T_j(k) -Y_j(k)]\ S_j'(Y_j(k))\ Z_i(k) \quad (6)$$

$$\Delta J_{ij}(k) = R_1\ X_i(k-1) \quad (7)$$

$$\Delta B_{ij}(k) = R_1\ U_i(k) \quad (8)$$

$$R_1 = C_i(k)\ [T(k)-Y(k)]\ S_j'(Z_j(k)) \quad (9)$$

Where: T is a target vector with dimension L; [T-Y] is an output error vector also with the same dimension; R_1 is an auxiliary variable; $S_j'(x)$ is the derivative of the activation function, which for the hyperbolic tangent is $S_j'(x) = 1-x^2$. The stability of the learning algorithm is proved in (Baruch *et al.*, 2002), and it is applied for a DC motor control.

2.2 Hierarchical Fuzzy-Neural Multi-Model

For complex dynamic systems identification, the fuzzy rule of (Takagi and Sugeno, 1985) admits to use in the consequent part a crisp function, which could be a static or dynamic (state-space) model. Some authors, referred in (Baruch, *et al.*, 1998; Mastorocostas and Theocharis, 2002), proposed as a consequent crisp function to use a NN function. In (Baruch *et al.*, 1998, 2001b), it is proposed as a consequent crisp function to use the RTNN model. The fuzzy rule of the proposed model is given by:

$$R_i\text{: IF x is } A_i \text{ THEN } y_i\ (k+1)= N_i\ [x(k), u(k)], \quad (10)$$

$$i=1,2,..,P$$

Where: N_i (.) denotes the RTNN model, given by equations (1) to (3); i -is the model number; P is the total number of models, corresponding to *Ri*. In the case when the intervals of the variables, given in the antecedent parts of the rules are not overlapping, the output of the model is a simple sum of the rule consequences, and this simple case, called fuzzy-neural multi-model, has been considered in (Baruch *et al.*, 1998, 2001b). In the general case, when the membership functions are overlapping, the output of the fuzzy neural multi-model system is given by the following equation:

$$Y= \Sigma_i\ w_i\ y_i = \Sigma_i\ w_i\ N_i(x,u) \quad (11)$$

Where w_i are weights, obtained from the membership functions, (see Baruch *et al.*, 2001b). As it could be seen from the equation (11), the output of the approximating fuzzy-neural multi-model is obtained as a weighted sum of RTNN functions, given in the consequent part of (10). The output of the upper level of the Fuzzy-Neural Hierarchical Multi-Model (FNHMM) is a complete weighted sum, given by (11), and the weighted summation is performed by a RTNN model, which introduced some kind of filtration of the outputs of the lower level RTNN's. So (11) is converted in the next discrete-time nonlinear dynamic equation:

$$Y(k+1) = N[x(k), (\Sigma_i w_i y_i (k))] =$$

$$N[x(k), (\Sigma_i w_i N_i (x_i (k), u_i (k)))] \quad (12)$$

3 ADAPTIVE FUZZY-NEURAL CONTROL SCHEMES

3.1 An Inverse Model Adaptive FNHMM Control Scheme

The main control objective here is to build an inverse model of the plant in such a way that the output of the plant tracks the system reference. It is obvious that the control here as an open loop feedforward learning control. The block-diagram of this control is given on Figure 1. It contains a FNHMM identifier (FNHMMI), which identifies the Jacobean of the plant, and a FNHMM feedforward controller (FNHMMC). The output of the plant and the reference signal are normalized in the interval [+1, -1] and divided in the same three overlapping intervals corresponding to its membership functions (positive, negative, and zero). The structure of the FNHMM identifier is given on Figure 2. The local and global errors of identification and control used for RTNNs learning are given by the following equations:

$$e_i(k) = y_{Pi}(k) - y_{ii}(k);\ e(k) = y_p(k) - y_i(k) \quad (13)$$

$$e_{ci}(k) = R_i(k) - y_{Pi}(k);\ e_c(k) = R(k) - y_p(k) \quad (14)$$

The FNHMMI has two levels – Lower Hierarchical Level (LHL), and Upper Hierarchical Level (UHL). The LHL is composed of three parts: 1) Fuzzyfication, where the plant output signal is divided in three intervals μ : positive [1, -0.5], negative [-1, 0.5], and zero [-0.5, 0.5]; 2) Lower Level Inference Engine (LLIE), which contains three (Takagi and Sugeno, 1985) TS - fuzzy rules, given by (10), and operating in the three intervals, and three RTNNs, learned by the local errors of identification (13); 3) Upper Level Defuzzyfication (ULD) which consists of one RTNN, learned by the global error of identification (13). This RTNN performs a filtered weighted summation of the outputs of the lower level RTNNs. The learning and functioning of both levels is independent.

The block-diagram of the FNHMM feedforward controller is given on Figure 3. During the learning, the control errors are attenuated by the inverse of the identified plants gain. The FNHMM feedforward controller contains the same elements as the FNHMM identifier. They are: fuzzyfication of the plant output and the reference signal; lower level inference engine, which contain the same number of rules and RTNNs, learned by the local errors of control (14); upper level defuzzyfication done by an upper level RTNN, learned by the global error of control (14).

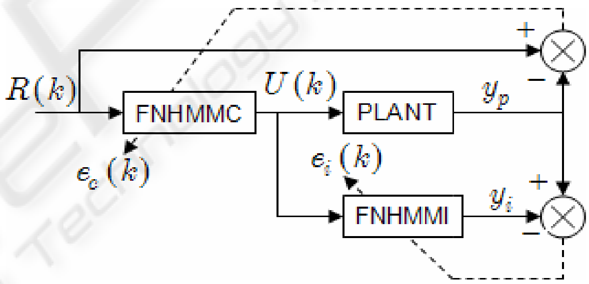


Figure 1: Block diagram of the inverse plant model control using FNHMM identifier and FNHMM feedforward controller

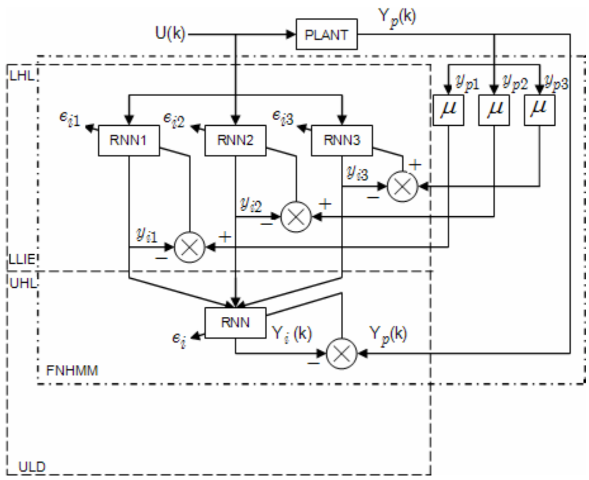


Figure 2: Block diagram of the Fuzzy Neural Hierarchical Multi-Model identifier

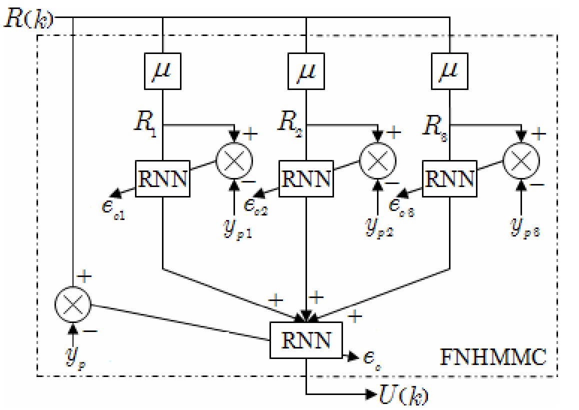


Figure 3: Block diagram of the FNHMM feedforward controller

3.2 A Direct Adaptive FNHMM Control Scheme

The structure of the system is given on Figure 4.

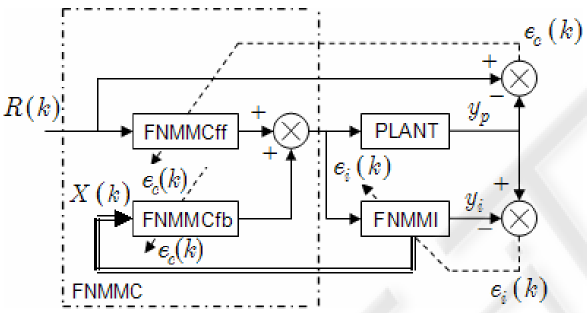


Figure 4: Block diagram of the direct adaptive neural control scheme using FNMMI, FNMMCfb and FNMMCff

It contains a FNHMM identifier (see Figure 2), FNHMM feedforward (see Figure 3) and feedback (see Figure 5) controllers. The FNHMM identifier and the FNHMM controllers contain fuzzyfier, a Fuzzy Rule-Based System (FRBS), a set of RTNN models and a RTNN used as defuzzyfier. The control fuzzy rules applied and the total control, issued by the FNMM control system are:

R_i: If x is A_i then $u_i = U_i(k)$, i=1, 2 ,.., L (15)

$$U_i(k) = - N_{fb,i} [x_i(k)] + N_{ff,i} [r_i(k)] \quad (16)$$

$$U(k)= \Sigma_i w_i U_i (k) \quad (17)$$

Where: r(k) is the reference signal; x(k) is the system state; $N_{fb,I}$ $[x_i(k)]$ and $N_{ff,I}$ $[r_i(k)]$ are the

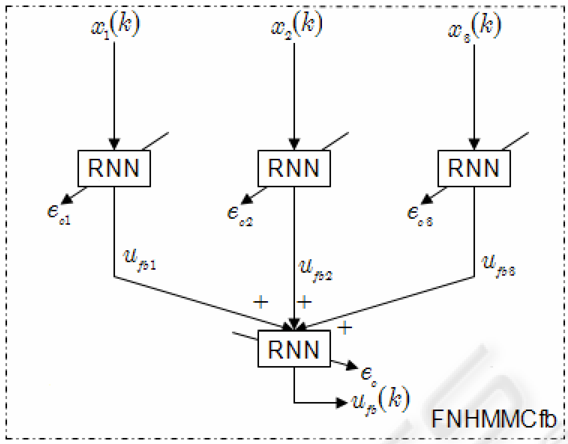


Figure 5: Block diagram of the FNMMC feedback controller

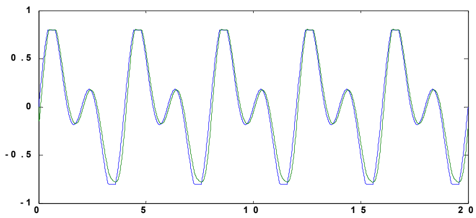
feedforward and feedback parts of the fuzzy-neural control, performed by RTNN functions, and w_i are weights, obtained from the membership functions, corresponding to the rules (15). As it could be seen from the equation (17), the control could be obtained as a weighted sum of controls, given in the consequent part of (15). In the case when the intervals of the variables, given in the antecedent parts of the rules, are not overlapping, the weights obtain values one and the weighted sum (17) is converted in a simple sum. From Figure 5 it is seen that the FNHMM identifier approximates the plant using three RTNNs, working in three overlapping intervals, corresponding to the three membership functions (positive, negative, and zero). The state vector issued by each RTNN is entry of a feedback FNMM controller and the FNHMM feedforward controller complements the control part. The defuzzification level of both control parts is performed by RTNNs (see Figures 3 and 5).

4 SIMULATION RESULTS

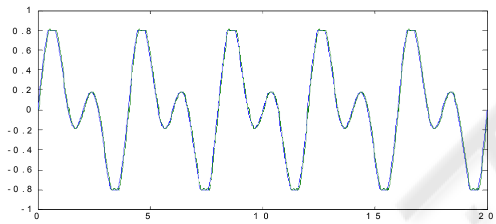
Let us consider a DC-motor - driven nonlinear mechanical system, taken from (Baruch, et al., 2001b), which has the following friction parameters (Lee and Kim, 1995): α = 0.001 m/s; F_s^+ = 4.2 N ; F_s^- = - 4.0 N; ΔF^+ = 1.8 N ; ΔF^- = - 1.7 N ; v_{cr} = 0.1 m/s; β = 0.5 Ns/m. Let us also consider that the position and the velocity measurements are taken with period of discretization To = 0.01 s; the system gain is ko = 8; the mass is m = 1 kg, and the load disturbance depends on the position and the velocity ($ld(t) = ld_1q(t) + ld_2v(t)$; ld_1 = 0.25; ld_2 = - 0.7). So the discrete-time model of the 1-DOF mass mechanical system is:

$$x_1(k+1) = x_2(k)$$
$$x_2(k+1)=-0.025x_1(k)-0.3x_2(k)+0.8u(k)-0.1fr(k) \quad (18)$$
$$v(k) = x_2(k) - x_1(k) \quad (19)$$
$$y(k) = 0.1\, x_1(k) \quad (20)$$

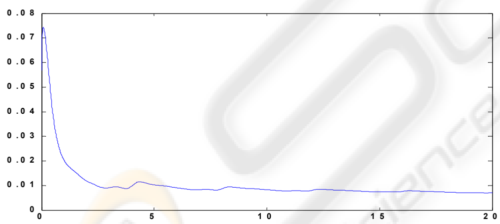
Where fr(k) is the friction force. Comparative results of plant control for both schemes, obtained using single RTNNs and that - using FNHMMCs, are given on Figure 6 a,b,c,d and Figure 7 a,b,c,d. For sake of comparison, simulation results obtained using a fuzzy controller, are given on Figure 8 a,b.



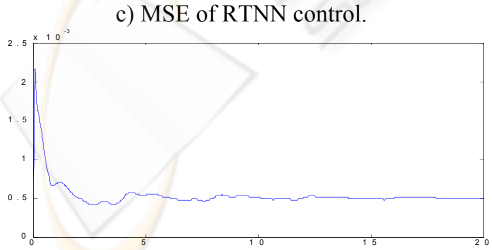
a) Comparison of the reference signal and the output of the plant controlled by one RTNN.



b) Comparison of the reference signal and the output of the plant controlled by FNHMMC.

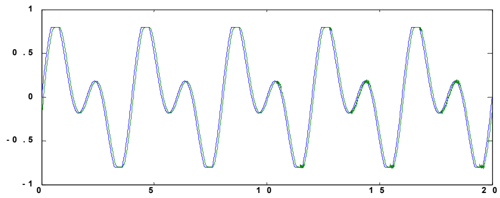


c) MSE of RTNN control.

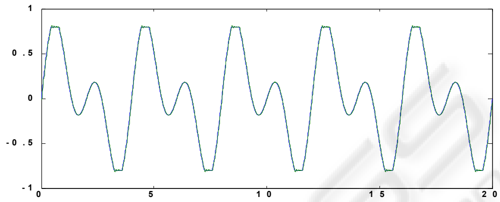


d) MSE of FNHMM control.

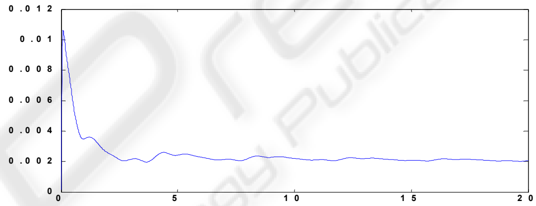
Figure 6: Trajectory tracking control results obtained with one RTNN feedforward controller and with a feedforward FNHMMC



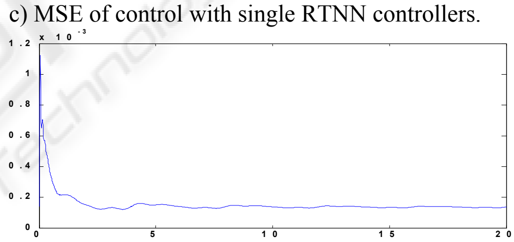
a) Comparison of the reference signal and the output of the plant, using single RTNN controllers.



b) Comparison of the reference signal and the output of the plant using FNHMMC.



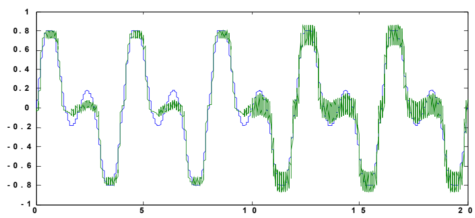
c) MSE of control with single RTNN controllers.



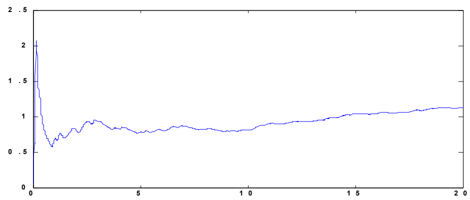
d) MSE of control with a FNHMMC

Figure 7: Trajectory tracking control results obtained with single RTNN feedforward/feedback control and with a feedforward/feedback FNHMMCs

Values of the Means Squared Error of identification and control using FNHMMs, single RTNNs, and fuzzy control, are given on Table 1.



a) Comparison of the reference signal and the output of the plant.



b) MSE of control.

Figure 8: Trajectory tracking control results obtained using a fuzzy controller

Table 1: Mean Squared Error of identification and control

Name	FNHMM vs. single RTNN
Systems identification:	0.08% vs. 0.27%
Feedforward control:	1.5% vs. 2.3%
Feedforward plus feedback direct adaptive control:	0.41% vs. 2.7%
Fuzzy control:	5.8% (does not use NNs)

From Figures 6, 7, 8 and the MSE% data from Table 1, we could conclude that: the systems identification using FNHMM gives better results than that using only one RTNN; the control schemes which use FNHMMC works better than that using one RTNN; the FNHMM feedforward/feedback direct adaptive control gives better results with respect to the FNHMM feedforward control; the fuzzy control is worse with respect to the neural control, especially when the friction parameters changed.

6 CONCLUSIONS

A FNHMM for identification and control of complex nonlinear plants is proposed. Two control schemes of FNHMM has been experimented and compared with a respective single-RTNN and fuzzy control. The comparison of identification results for a 1 DOF mechanical system with friction show that the FNHMM identifier has a better performance with respect to the identification using one RTNN. The same is valid for the schemes of control. The better control is the feedforward/feedback control and the worse control is the fuzzy control.

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