MODELS IDENTIFICATION AND ADAPTIVE CONTROL OF THE FLYING OBJECTS USING NEURAL NETWORKS

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Abstract: - In this paper one presents some hierarchy structures for models identification and adaptive control using neural networks. One presents a new control system with leading system's identification (presented in fig.5), which may be made particular using as leading system longitudinal dynamic of aircrafts. A simulation program for identification and adaptive control of the longitudinal movement has been obtained; with this program the neural network weights of the adaptive regulator has been calculated and different time characteristics of the closed loop system has been plotted.

Key-Words: - identification, adaptive, neural network, aircraft

1 Adaptive control systems with neural networks

Neural regulator must achieve the inverse function (A^{-1}) of the leading system (A). Such adaptive control systems, using neural networks, are presented in [1], [2], [3], [4]. A control system with neural regulator is the one presented in fig.1.

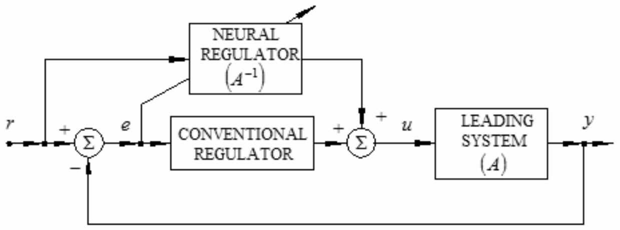

Fig.1 Control system with conventional regulator and neural regulator

The conventional regulator makes time initialization, while the neuronal regulator has a minimum influence in the control system. Regulator parameters' modification in the learning step is made until error of system e tends to zero.

In fig.2 another control system with neural regulator is presented; here r is the system's reference, e - difference between real command u and the imposed one u^*.

In fig.3 a control system with 3 levels is presented. The first level has an external feedback (conventional loop). The second level, consisting of neural network 1, learns the leading system's dynamic. The third level, consisting of neural network 2, learns how to model the inverse dynamic of the leading system. During learning, level 2 takes the role of the conventional loop. So, the neural network 1 identifies the leading system's dynamic, and neural network 2 identifies the inverse dynamic (the main regulator).

Excluding levels 2 and 3 other 2 control structures are obtained.

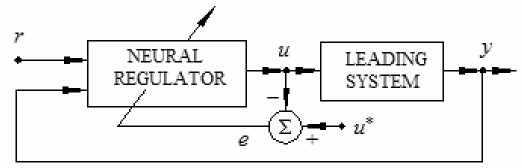

Fig.2 Control system with neural regulator

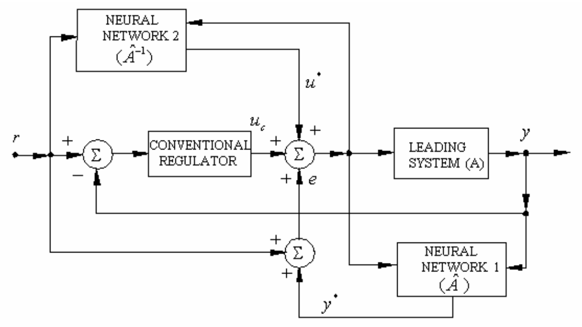

Fig.3 Hierarchy structure with 3 levels

The system in fig.4 allows indirect learning; the neural networks are the same. The purpose is to determine the command $u(k)$ so that $y(k) \to r(k)$. The weights of the two networks are permanently modified by error $e(k)$ (the difference between the two neural networks' outputs).

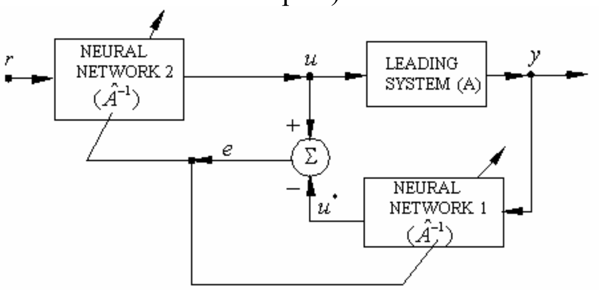

Fig.4 Control system with indirect learning rule

Another adaptive control system given by the authors of this paper is depicted in fig.5. In the identification stage, the system is open on the direct way (the command applied simultaneously to leading system and neural network is made by a signal generator block; the switch is on identification mode). After identification the switch is on R position – automat control; $u = u_R = u_c + u'$, where u_c is the command signal from the conventional regulator; the neural regulator must model the inverse of the neural network's function; that means the neural regulator's model must be $\hat{A}^{-1}$; $\hat{A}$ is the neural network's model for the leading system's model A. The input for neural regulator is error e' of the adaptive control system; $e' = r - \hat{y}, r$ is the system's reference and $\hat{y}$ - neural network's output.

Neural regulator may be made using a feed – forward neural network based on mean square error's minimization; the error is $e'' = u^* - u'$, where u^* is the imposed output of the neural regulator and u' - the current output of the regulator.

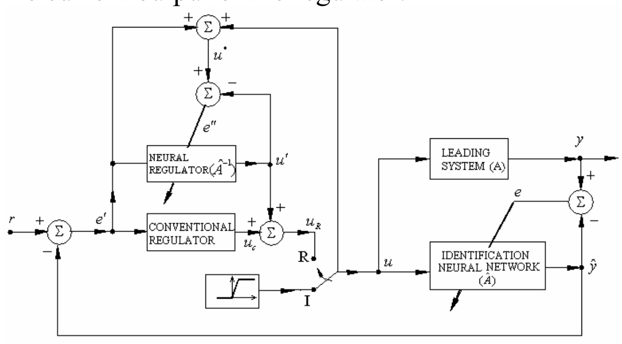

Fig.5 Hierarchy structure for identification and adaptive control

For u^* calculus, one considers that error e'' and e' tend to zero in stationary regime. So, one imposes that $e' \cong e'' = u^* - u$ tends to $u'(u_c \to 0)$; it results

$$u^* \cong e' + u' \cong e' + u, \qquad (1)$$

Neural regulator's train stops when $e'' \to 0(e' \to 0)$; in this moment, adaptive control system command has the property $u \to u^*(u_c \to 0)$. On the direct way of the adaptive control system one achieves the inverse of the feedback function $\left(\hat{A}^{-1}\hat{A} \cong 1\right)$.

In the switching moment (the switch changes identification position with the control one (R)), the initial value for u is the input of the identification neural network from that moment (this input is given by the signal generator).

2 Adaptive stabilization of the aircrafts' attitude

Using the control system from fig.5, one may achieve aircrafts' longitudinal movement stabilization; the leading system is the longitudinal movement's dynamic of the aircraft described by the model from [5].

The simulation program for identification of the longitudinal movement is presented in Appendix.

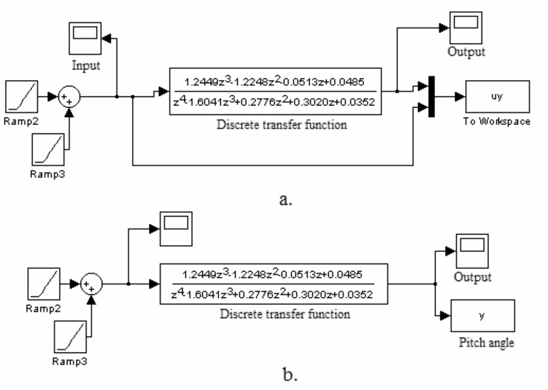

Fig.6 Matlab/Simulink models for neural network (a) and leading system (b)

The input of the leading system (longitudinal movement's model) and of the neural network is ramp type on an interval of 2 seconds with 0.05 rad/sec slope; the ramp is followed by a saturation zone with amplitude $u = \delta_p = 0.1$ rad. Matlab/ Simulink model of the neural network and the leading system are presented in fig.6.

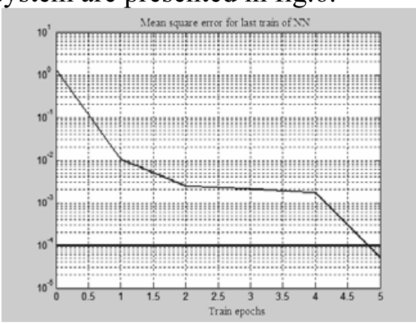

Fig.7 Mean square error

Simulation program achieves neural regulator's train using the same algorithm as the one for the leading system's identification. The train of neural regulator and identification neural network stops when $e'' \to 0$ (the moment when $e' \to 0$) and $e \to 0$; this is when $\hat{y} \to y \to r$; one has chosen $r = 0.20935$ rad and $k_c = 0.7$ (gain coefficient of the regulator) [6].

Simulation program plots the mean square error for identification neural network after training in rapport with number of training epochs. In fig.8 leading system's output $y(t)$ (with little circles) and neural network's output $\hat{y}(t)$ (with continuous line) are plotted [7].

In fig.9 signals $u^*(t)$ - reference signal and $u'(t)$ - neural regulator's output are plotted; in fig.10 one presents the command signal of the adaptive leading system $u(t)$ and in fig.11 one presents adaptive control system's error $e'(t)$; because $e'(t) \to 0$ it results $u_c = k_c e' \to 0$ and $u(t) \to u'(t) \to u^*(t)$. The fact that $e' \to 0$ is confirmed by fig.12 $(\hat{y}(t) \to r(t))$; one has chosen the reference signal $r = \text{const.} \cong 0.2$ rad.

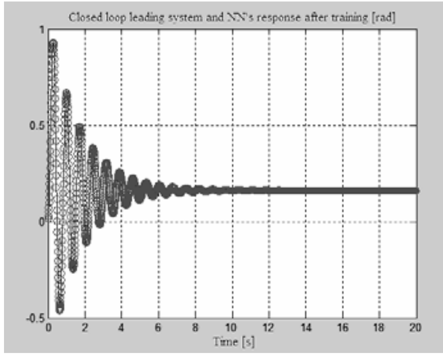

Fig.8 Leading system and NN's response after training

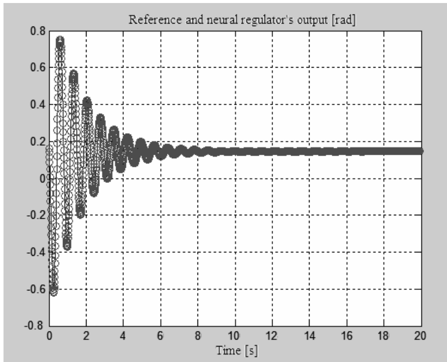

Fig.9 Signals $u^*(t)$ and $u'(t)$

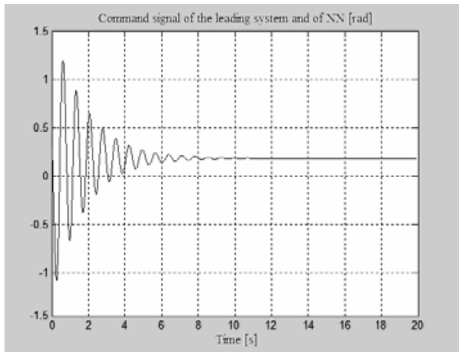

Fig.10 Command signal $u(t)$

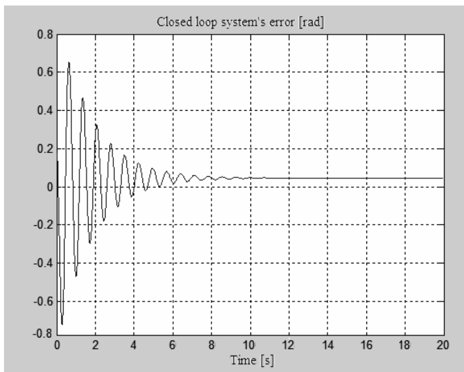

Fig.11 Adaptive control system's error

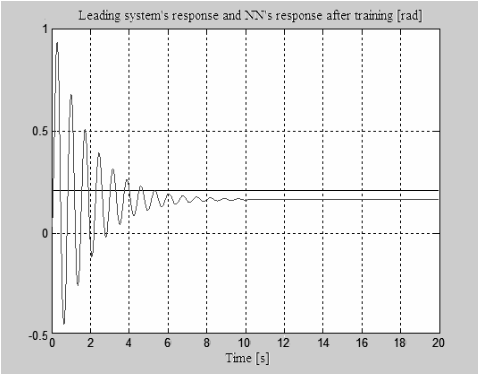

Fig.12 Signals $r(t)$ and $\hat{y}(t)$

After training one obtains the following weights for the neural network

$$W_1 = \begin{bmatrix} -0.2257 & 1.3670 & -1.6547 & -20.5813 \\ 1.4443 & -1.1286 & 0.6718 & 5.6728 \\ 0.4096 & 0.1874 & 1.1743 & 32.6221 \\ -0.2822 & -1.3914 & 1.7408 & -20.816 \\ 0.0152 & 0.2540 & -1.1176 & 28.0938 \end{bmatrix}; \quad (2)$$

$$W_2 = \begin{bmatrix} -0.9948 & 0.2614 & 0.2337 & 0.3140 & -0.6736 \end{bmatrix};$$

$$B_1 = \begin{bmatrix} 3.5007 \\ -1.8569 \\ -2.5351 \\ 2.9401 \\ -3.6811 \end{bmatrix}; B_2 = 0.5451,$$

and after training of the regulator

$$w_1 = \begin{bmatrix} -2.2990 & 3.5702 & 2.0010 & -1.4017 \\ -0.0532 & -0.8236 & -2.8633 & -2.6471 \\ 2.0321 & 1.3235 & -1.3111 & 2.5900 \\ -0.4527 & 1.5959 & -1.6810 & 0.0107 \\ -0.9301 & -0.3484 & 1.3832 & 0.7444 \end{bmatrix}; \quad (3)$$

$$w_2 = \begin{bmatrix} 0.1880 & -0.0120 & 0.0367 & -2.0067 & -0.2235 \end{bmatrix};$$

$$b_1 = \begin{bmatrix} .4376 \\ -1.6991 \\ 0.1621 \\ 0.3783 \\ -1.1676 \end{bmatrix}; b_2 = 0.3585.$$

3 Appendix

```
clear all;close all;a=0.1;contor=1;Q=20;
for contor=1:Q
z=menu('Continue or not the system’s simulation',...
'Continue training process of the neural network and regulator',...
'Escape training process of the neural network and regulator');
disp('')
if z==1
sim('longrampa1');sim('longrampa2');
ytr=y;M=size(uy(:,1));M(:,[2])=[];
ny=3;nu=1;d=0;nh=5;Pn=[uy(1:M-3,1)';
uy(2:M-2,1)';uy(3:M-1,1)';uy(3:M-1,2)'];
Tn=y(4:M,1)'; Z=[min(Pn(1,:)) max(Pn(1,:));
  min(Pn(2,:)) max(Pn(2,:));
  min(Pn(3,:)) max(Pn(3,:));
  min(Pn(4,:)) max(Pn(4,:))];
net=newff(Z,[5 1],{'tansig' 'purelin'});
net.trainParam.epochs=3000;
net.trainParam.goal=0.0001;
net = train(net,Pn,Tn);grid; Y2 = sim(net,Pn);
W1=net.iw{1,1};W2=net.lw{2,1};
B1=net.b{1};B2=net.b{2}
for i=1:size(Y2,2)
   r(i)=0.20935;
end
Ep=r-Y2; u=uy(1:size(Ep,2),2)'; Us=Ep+u; Kc=0.7;
Uc=Kc*Ep; N=size(Us,2);
Pc=[Us(1:N-3);Us(2:N-2);Us(3:N-1);Ep(3:N-1)];
Tc=Us(4:N); Z=[min(Pc(1,:)) max(Pc(1,:));
  min(Pc(2,:)) max(Pc(2,:));
  min(Pc(3,:)) max(Pc(3,:));
  min(Pc(4,:)) max(Pc(4,:))];
net = newff(Z,[5 1],{'tansig' 'purelin'});
net.trainParam.epochs=3000;net.trainParam.goal=0.
0001; net = train(net,Pc,Tc);grid;
Up = sim(net,Pc); w1=net.iw{1,1};w2=net.lw{2,1}
b1=net.b{1};b2=net.b{2}; Ur=Up+Uc(1:N-3);
 u=Ur; N=size(u,2); a=u(length(u));
contor=contor+1; else break
contor=Q;
end   %if
end   %for
h=figure;t=1:length(Y2); plot(t,Y2,'b',t,Tn,'ro');grid;
title('Leading system’s response in closed loop and of NN after last training step [rad]'); xlabel('Timp[s]');
h=figure; t=1:length(Up);plot(t,Up,'b',t,Tc,'ro');grid;
title('The reference and neural regulator’s output [rad]'); xlabel('Timp[s]');h=figure; t=1:length(Y2);
plot(t,r,'k',t,Y2,'r');grid;
title('Leading system’s reference and NN’s response after training [rad]'); xlabel('Timp[s]'); h=figure;
t=1:length(u);plot(t,u);
grid;title('Command signal of the leading system an of NN [rad]');  xlabel('Timp[s]');h=figure;
t=1:length(Ep);plot(t,Ep);grid;title('System’s
deviation in closed loop [rad]');xlabel('Timp[s]');
```

4 Conclusions

The paper presents adaptive control systems with neural networks, with off – line identification of the leading system’s models using neural networks. A new variant of control structure for identification and adaptive control is presented; this has good application to longitudinal movement stabilization. The results obtained by numeric simulation validate theoretical issues.

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