Nonlinear System Controller Based on a Self-Organizing Map

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Abstract: This paper presents a controller based on Kohonen's Self-Organizing Map (SOM), used in commanding the time varying systems with uncertainties task. First, it was applied a reduction procedure of the initial set of parameters using an unsupervised pattern recognition technique. After this a SOM was trained using the minimized set of data obtained above. An application of a missile-target tracking was implemented using the mentioned method, and the results are compared with those obtained in a classical approach.

1. Introduction

When all apriori information about the controlled process is known, there can be designed an optimal controller using deterministic optimization techniques [1][2][3][4]. When the apriori information required is unknown or partially known an optimal design is used. In this case we can discuss two different approaches in solving the problem. One approach is to design a controller based only on the amount of information available, the unknown information being ignored or approximated with a known value given by a performance criterion (for example, mini-max criterion). In this case the systems designed are, in general, suboptimal [5][6][7][8]. The second approach consists of designing a controller able to estimate the unknown information, so if it is possible to approach gradually the true information, then the designed controller approaches the optimal one. In this case, it could be said that the controller learns during the process what decisions will make in the following. A basic block diagram for a *learning control system* is shown in Fig. 1, where the dynamical system under control **u** is disturbed by the perturbation **z**, assumed to be unknown or partially known. In classical theory the unknown values are estimated to decrease the error between the true value and the designed one, therefore in the *learning control theory* exists a *teacher* which, using a certain rule, teaches to the controller the commands necessary in reaching the expected goal.

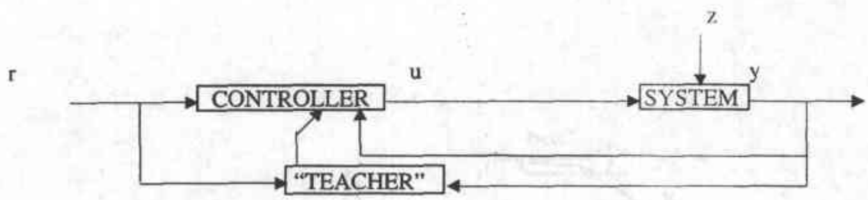

Fig.1 Block diagram of a learning control system

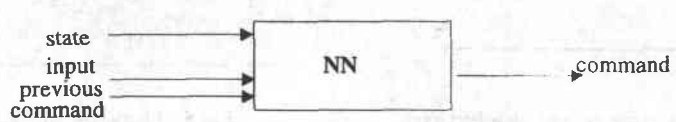

Fig.2 Neural network controller scheme

2. Neural networks applied to control uncertain nonlinear dynamical systems

For *implementing a controller* we used a supervised approach of the Kohonen's SOM. Designing a controller means to find the values of the actual control using the input values, the state values and the previous control. So, in this case the network's output must be the current control and the inputs are the state, the input and the previous control (Fig. 2).

Supposing the inputs $x_1 \ldots x_K$, represented by a k-dimensional vector **X** in the feature space Ω_X [17], and $\omega_1 \ldots \omega_M$ be the M classes of the control situations, the control operation can be interpreted as a partition of the k-dimensional space Ω_X into M decision regions corresponding to the M control classes. To determine the M control classes a clustering method based on the minimum Euclidean distances between vectors and classes' prototype [18] was applied (Fig.3). We can say that all vectors of the same class, which means that the distance between vectors is lower than a threshold D, have approximately the same features and we can approximate their controls with the control corresponding to the center of the class.

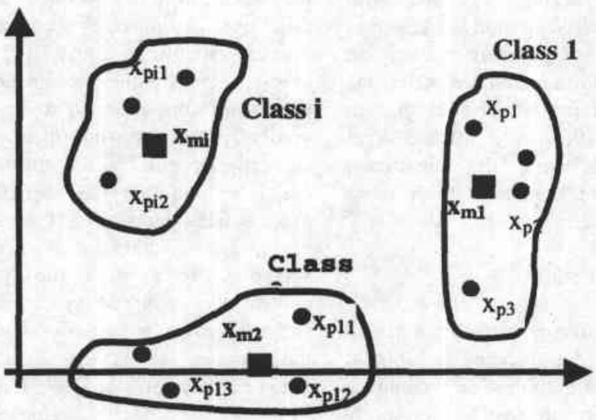

Fig.3 Isodata clustering method used for reducing the initial set of data

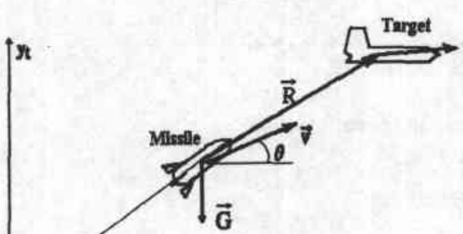

Fig.4 System's parameters and attached axes

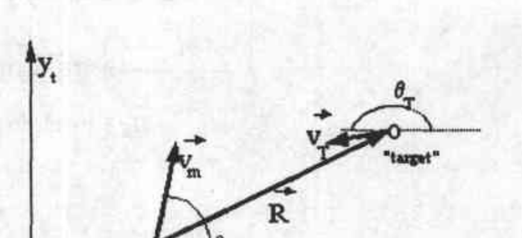

Fig.5 The missile movement in vertical plane

4. Application

In this section we design the neural control of a missile which track a target with an unknown dynamics and evolution. The system's parameters and axes are attached as shown in Fig.4 and 5.

The general case of missile's movement is described by a differential system with 23-equation [21].

$$(\Sigma_m)\begin{cases}\dot{\theta}_m = 5.23\alpha_m \\ \dot{\alpha}_m = p_m \\ \dot{p}_m = -5.88\,p_m - 728.43\,\alpha_m - 529.5\,\delta_m \\ \dot{\Phi} = \dfrac{V_m}{R}\sin(\Phi - \theta_m) - \dfrac{V_T}{R}\sin(\Phi - \theta_T)\end{cases}$$

$$(\Sigma_T)\begin{cases}\dot{\theta}_T = 1.62\,\alpha_T \\ \dot{\alpha}_T = p_T \\ \dot{p}_T = -2.505\,p_T - 572.5\,\alpha_T - 300.5\,\delta_T\end{cases}$$

Therefore, designing a controller using classical methods means to solve numerical and in real-time this differential system. Using the neuronal network, which directly makes the correspondence between the input and the output values, after it was trained, eliminates this disadvantage.

The distance missile-target R, the line of sight angle Φ and the tilt angle of the trajectory θ, parameters depending on the previous command, are the inputs of the SOM, so the network has 3 input nodes.

The SOM's output is the next command with values between -0.56 and 0.56 (due to the maximum admissible overload condition $n = \pm 10g$). The output range was divided into 11 intervals, each of them corresponding to a class of command. We choose a 5x5 square output layer, so after training the Kohonen's SOM each class of command is represented by a cluster of output neurons.

5. Conclusions

In Fig.6 and Table 1 are presented the results of the simulation using the controller based on a neural network described above. The results are compared with those obtained using a robust controller [23]. Speaking from the quality point of view, which is the catching time of target, we can see that our method with neural network is better than the classical one (the robust controller)

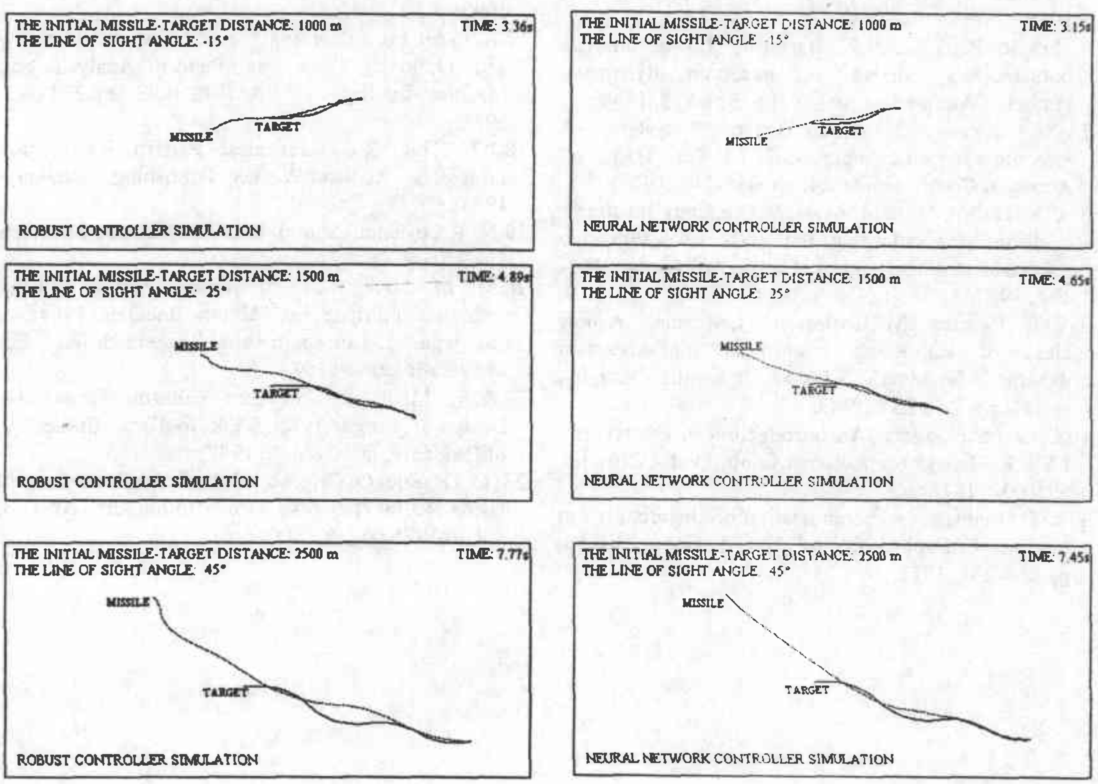

Fig.6 Simulation of the classical and neural controller

Table 1 Comparison of the classical and neural controller

The initial missile-target distance [m]	The line of sight angle [°]	Time [s]	
		Robust controller	Neural controller
1000	-15	3.36	3.15
1500	25	4.89	4.65
2500	45	7.77	7.45
2500	-50	7.23	6.6
3000	-20	9.78	9.69

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