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A neural network for the identification of the dynamic behaviour of a wheelchair

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Abstract. A new architecture for a recurrent radial base neural network is presented in this article. This architecture is composed for neurons with feedback via an FIR filter at the output where there is another FIR filter. Its main application is as an identifier of physical systems with a memory, as it has information on previous states in the coefficients of the filters designed. The coefficients of the filters are adjusted using a descent by gradient algorithm, the stability of the training process is demostrated and this method is used to identify a wheelchair.

1. Introduction

A new type of neural network based on RBF's is described in this article. These neurons have a radial function (Gaussian type transfer function) with a feedback between their output and their input by means of a FIR filter and which have a new FIR filter located at their output, in the form of a synaptic connection. In this way, it is not necessary to add external delays to the neural network in order to identify recurrent systems, since the information on previous states is implicitly contained in the coefficients of the FIR filters. This neural model can be considered as an hybrid scheme between the model proposed in [1] with synatic filters and the model proposed in [2] with feedback filters to each neuron.

2. Neural Network Architecture, Training and Stability

The model for the recurrent radial base neural network in Figure 1 is considered in this article, where it is shown the proposed architecture. In this model, feedback exists from the output of each neuron to its own input, using a FIR filter ($F_{im}^{R}(z)$); another FIR filter is introduced at the output of this neuron at the same time ($F_{ip}^{W}(z)$), which is independent of the first one, thus making up the synaptic connection between each neuron and the overall network output. The outputs of the synaptic filters and the feedback filters are respectively:

$$y_{ip}(k) = \sum_{j=0}^{S\ 1} a_{ipj}^{w} \cdot g_i(k-j) \qquad x_{im}'(k) = \sum_{t=1}^{R} a_{imt}^{R} \cdot g_i(k-t) \quad i = 1,...M; \quad m=1,2 \ (1)$$

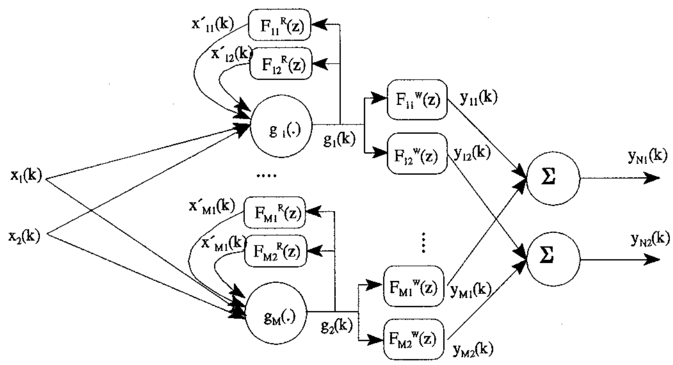

Figure 1. Neural network model

The output of the i[th] neuron at moment k is given by:

$$g_i(k) = e^{-\frac{(x_1(k) + x'_{i1}(k) - C_{i1})^2 + (x_2(k) + x'_{i2}(k) - C_{i2})^2}{\sigma^2}} \tag{2}$$

where x_{im}' is the output of the feedback filter that connects the output of the neuron to its own input. The neural network output is

$$y_{Np}(k) = \sum_{i=1}^{M} y_{ip}(k) \qquad p = 1,2 \tag{3}$$

2.1 Training Algorithm

Once the structure of the neural network has been established, all the adjustable parameters of the network (filter coefficients) are adjusted in such a way to minimize the error function E(k). The input signal is propagated through the network in each training cycle until the overall network output is obtained. Then the gradients between the error function and the adjustable parameters are calculated. This second step is performed in the reverse direction, i.e., from the output to the input. The instantaneous error is defined as:

$$E(k) = \frac{1}{2}(y_{N1} - y_{d1})^2 + \frac{1}{2}.(y_{N2} - y_{d2})^2 \tag{4}$$

The expresion for the adjustment of the coefficients of the synaptic filters is:

$$\Delta a_{ipj}^{w} = -\alpha_1.\frac{\partial E}{\partial a_{ipj}^{w}} = -\alpha_1.\frac{\partial E}{\partial y_{Np}}.\frac{\partial y_{Np}}{\partial y_{ip}}.\frac{\partial y_{ip}}{\partial a_{ipj}^{w}} = -\alpha_1.(y_{Np} - y_{dp}).g_i(k-j) \tag{5}$$

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And for the coefficients of the feedback filters:

$$\Delta a^R_{imt} = -\alpha_2 . \frac{\partial E}{\partial a^R_{imt}} = -\alpha_2 .[(y_{N1} - y_{d1}).a^w_{i10} + (y_{N2} - y_{d2}).a^w_{i20}] . \frac{\partial g_i}{\partial a^R_{imt}} \tag{6}$$

Being:

$$\frac{\partial g_i}{\partial a^R_{imt}} = \frac{\partial g_i}{\partial x'_{im}} . \frac{\partial x'_{im}}{\partial a^R_{imt}} = \frac{\partial g_i}{\partial x'_{im}} .[g_i(k-t) + \sum_{s=1}^{R} a^R_{ims} . \frac{\partial g_i(k-s)}{\partial a^R_{imt}}] \tag{7}$$

2.2. Stability

The follow Lyapunov function is considered [3]:

$$V(k) = \frac{1}{2}.(y_{N1}(k) - y_{d1}(k))^2 + \frac{1}{2}.(y_{N2}(k) - y_{d2}(k))^2 = \frac{1}{2}.e_1(k)^2 + \frac{1}{2}.e_2(k)^2 \tag{8}$$

The change in the function can be expressed as follows:

$$\Delta V(k) = V(k+1) - V(k) = \Delta e_1(k).[e_1(k) + \frac{1}{2}.\Delta e_1(k)] + \Delta e_2(k).[e_2(k) + \frac{1}{2}.\Delta e_2(k)] \tag{9}$$

If the **W** vector contains the adjusting coefficients of the network:

$$\Delta e_1(k) \approx [\frac{\partial e_1(k)}{\partial \mathbf{W}(k)}]^T . \Delta \mathbf{W}(k) \qquad \Delta e_2(k) \approx [\frac{\partial e_2(k)}{\partial \mathbf{W}(k)}]^T . \Delta \mathbf{W}(k) \tag{10}$$

The variation of the energy function is:

$$\begin{aligned} \Delta V(k) = & -e_1(k)\alpha.\|\frac{\partial y_{N1}(k)}{\partial \mathbf{W}(k)}\|^2 - e_2(k)^2\alpha.\|\frac{\partial y_{N2}(k)}{\partial \mathbf{W}(k)}\|^2 - \\ & 2.e_1(k).e_2(k).\alpha.(\frac{\partial y_{N1}(k)}{\partial \mathbf{W}(k)})^T.\frac{\partial y_{N1}(k)}{\partial \mathbf{W}(k)} + \\ & + \frac{1}{2}.[e_1(k).\alpha.\|\frac{\partial y_{N1}(k)}{\partial \mathbf{W}(k)}\|^2 + e_2(k).\alpha.[\frac{\partial y_{N1}(k)}{\partial \mathbf{W}(k)}]^T.\frac{\partial y_{N2}(k)}{\partial \mathbf{W}(k)}]^2 + \\ & \frac{1}{2}.[e_2(k).\alpha.\|\frac{\partial y_{N2}(k)}{\partial \mathbf{W}(k)}\|^2 + e_1(k).\alpha.[\frac{\partial y_{N2}(k)}{\partial \mathbf{W}(k)}]^T.\frac{\partial y_{N1}(k)}{\partial \mathbf{W}(k)}]^2 \end{aligned} \tag{11}$$

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To obtain negative increment in V(k):

$$0 < \alpha < \frac{1}{\|\frac{\partial y_{N1}}{\partial W}\|^2} \qquad 0 < \alpha < \frac{1}{\|\frac{\partial y_{N2}}{\partial W}\|^2} \tag{12}$$

In the proposed model:

$$W = [a^w_{110}\ ,\ \ldots\ w^w_{M2(S-1)}\ ,\ a^R_{111}\ ,\ \ldots\ a^R_{M2R}\ ]^T \tag{13}$$

The number of the sipnasis filters coefficients (a^w_{ipj}) is 2MS and the number of feedback filters coefficients is 2MR. For the sipnasis coefficientes:

$$\|\frac{\partial y_{N1}}{\partial a^w_{ipj}}\|_{m\acute{a}x} = 1 \tag{14}$$

For the feedback filters:

$$\|\frac{\partial y_{N1}}{\partial a^R_{imt}}\|_{m\acute{a}x} = \frac{M_d}{1-M_d.R} \tag{15}$$

If the following condition is met:

$$M_d = m\acute{a}x\ \|\ \frac{\partial g_i(k)}{\partial x'_i(k)}\ \| = \frac{\sqrt{2}}{\sigma}.e^{-\frac{1}{2}} < \frac{1}{R} \tag{16}$$

Considering the last expressions:

$$0 < \alpha < \frac{1}{2.M.S + (\frac{M_d}{1-M_d.R})^2.R.M.2} \tag{17}$$

3. Practical results

The described model was used for the identification of the dynamic behaviour of a wheelchair (Fig. 2) The aim is to obtain a good behaviour model that is also adaptive: network training must be effected while the chair is in operation: a parallel-parallel

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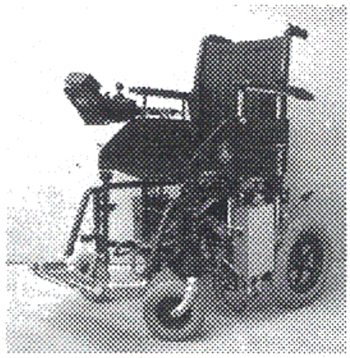

Figure 2. Wheelchair used in the tests

identification model is therefore most suitable applying two input signals u_R and u_L (corresponding to the voltage of the right and left wheel respectively). Two readings are thereby obtained, each indicating the speed of the right and left wheel (w_R w_L). In the first sampling cycle of the tests perfomed, all the neural network coefficients have random values (different in each experiment). In this case it is possible to observe the time needed for the network to identify the wheelchair correctly. The tests involved applying different signals to each of the chair's wheels (Figs. 3 to 6), distinguishing the speed of each wheel (-) and the output given by the corresponding network (..). In the experiments the following parameters were used to effect the identification: M= 16; R= 2; S= 2; σ = 2,2, α = 0,003; In figure 4it is shown when a person sat down in the chair, to shown the effect of the dinamical identificacion.

4. Conclusions

A real physical system was identified using a new model of recurrent neural network, which is characterized by the existence of an FIR filter, which provides feedback to each one of the neurons and another group of filters that act as synaptic connections between the output of each neuron and the overall output of the network. After obtaining the

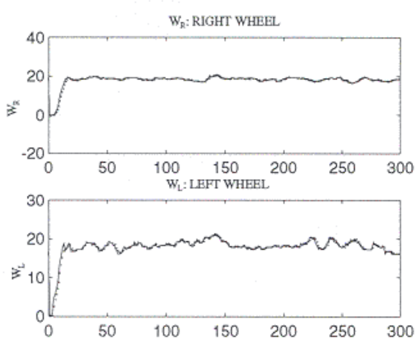

Figure 3.- Test 1

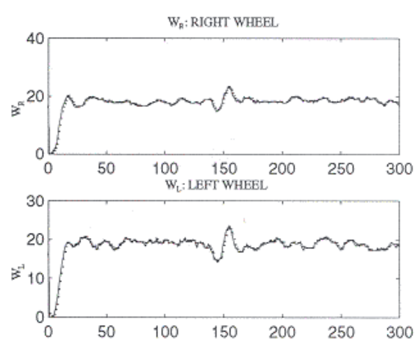

Figure 4. Test 2

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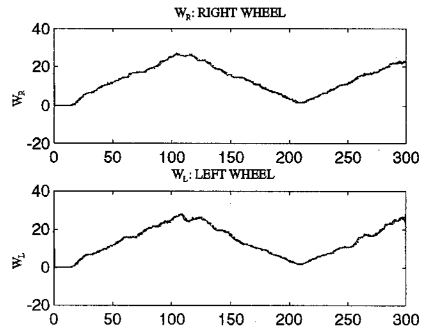

Figure 5. Test 3

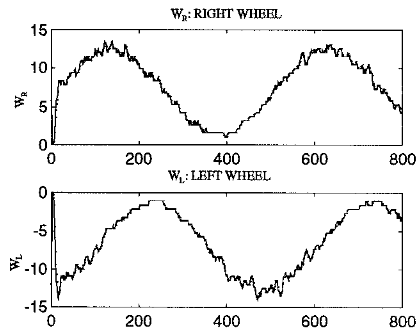

Figure 6. Test 4

formulae for the adjustment of network coefficients, the necessary conditions were found for assuring convergence during the learning process. The tests carried out prove that the proposed model works well: minimum identification error and high convergence speed.

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