A Modified Learning Algorithm for Backpropagation Network

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ABSTRACT

A modified backpropagation (MBP) algorithm is proposed in this paper. The MBP algorithm is based on the idea that both the error E_p and its change ΔE_p can be applied as information to update weights. It can be seen from Fig. 1 that when E_p curve is convex, the signs of E_p and ΔE_p slopes are the same. When E_p curve becomes concave, the signs are opposite. Therefore, if ΔE_p slope is added to or subtracted from E_p slope as appropriate, the network training is expected to speed up. This idea can be expressed as

Fig. 1. E_p and ΔE_p curves

$$\Delta w_{ij} = -\eta \frac{\partial E_p}{\partial w_{ij}} + \text{sign} \left(\frac{\partial \Delta E_p}{\partial w_{ij}} \right) \cdot \xi \cdot \frac{\partial \Delta E_p}{\partial w_{ij}} \quad (1)$$

where ξ is a constant defined as an *accelerator*. For clarity, we define i, j and k as the unit in output, hidden and input layers. The derivatives of ΔE_p with respect to w_{ij} and w_{jk} are given as

$$\frac{\partial \Delta E_p}{\partial w_{ij}} = \left[\frac{\partial^2 o_{pi}}{\partial w_{ij}^2} \cdot \frac{\partial E_p}{\partial o_{pi}} + \left(\frac{\partial o_{pi}}{\partial w_{ij}} \right)^2 \right] \Delta w_{ij} \quad (2)$$

$$\frac{\partial \Delta E_p}{\partial w_{jk}} = \sum_i \left[\left(\frac{\partial o_{pi}}{\partial w_{ij}} \cdot \frac{\partial o_{pi}}{\partial w_{jk}} + \frac{\partial E_p}{\partial o_{pi}} \cdot \frac{\partial^2 o_{pi}}{\partial w_{ij} \partial w_{jk}} \right) \Delta w_{ij} \right] \quad (3)$$

Simulations are carried out on the XOR, parity, encoding and symmetry problems. Results show that when compared to the conventional backpropagation (CBP) algorithm, MBP can reduce the training iterations by from 25% to 90%, depending on different problems.

Another attractive feature of MBP algorithm is that it is convergent when starting with equal or even zero initial weights. This eliminates the guesswork of finding proper initial weights for the network to avoid local minimum. Table 1 gives some of the MBP simulation results starting with zero initial weights. The CBP iterations listed in the table are the average of several training sessions with different random initial weights (η is the learning rate and α is momentum factor).

Table 1. MBP training with zero initial weights (compared to CBP training)

η	α	Training iterations in XOR problem		Training iterations in Symmetry problem	
		MBP ($\xi=10$)	CBP (average)	MBP ($\xi=4.0$)	CBP (average)
0.1	0.1	17380	57860	411120	532160
0.9	0.9	220	520	6080	8640