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IMPROVED RECOGNITION CAPABILITIES FOR GOAL SEEKING NEURON

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Indexing term: Neural networks

RAM based neural networks are a relatively new class of neural network which exhibit faster learning and greater ease of VLSI implementation than the traditional analogue models. Two RAM based neural models, the probabilistic logic neuron (PLN) and the goal seeking neuron (GSN), are simulated to determine their recognition capabilities. It is found that the PLN has very poor capabilities, whereas the GSN has widely varying capabilities due to the random nature of the GSN learning algorithm. A new GSN learning algorithm is presented which gives consistently good results.

Introduction: The vast majority of artificial neural network research and application deals with the traditional analogue neural model. Analogue networks have a number of advantageous characteristics, including intrinsic generalisation abilities. The disadvantages of analogue neural models typically include slow training and difficulty of VLSI implementation. RAM based neural networks are a relatively new class of neural network which overcome these disadvantages [1]. This Letter answers the question of whether RAM based neural networks can be made to exhibit, in some sense, the important generalisation ability of analogue networks.

The first popular RAM based neural model was the probabilistic logic neuron (PLN) proposed by Kan and Aleksander [2]. The PLN is a very simple model, and is therefore very easy to implement. GSN networks suffer, however, from the problems of nondeterministic response, saturation of learning space, and poor generalisation ability [3].

The goal seeking neuron (GSN) is a more complex RAM based neural model proposed by Filho *et al.* to overcome the limitations of the PLN [4, 5]. A GSN network has a deterministic response, makes more efficient use of the limited storage space of a RAM-based neuron, and has some intrinsic generalisation abilities.

Nonrandom learning: The operation of the GSN is deterministic, except for the learning state of the neuron. When there is more than one possible location to write the desired output value to, a random decision is made. This means that two identical GSN networks, trained with the same data, could have different recognition properties due to different decisions being made during the learn phase of the network.

It was found that to implement such a random decision would be difficult using digital logic, and would make the performance of the GSN network inconsistent in the manner mentioned above. For these reasons, the following alternative methods of choosing a location were evaluated as alternatives to the random method:

(1) choose the first applicable cell when arranged in numerical order of cell addresses

(2) If the desired output of the pyramid is 0, choose the applicable cell whose address is closest to 00 ... 0 (i.e. all 0s) in terms of Hamming distance; if the desired output of the pyramid is 1, choose the applicable cell whose address is closest to 11 ... 1 (i.e. all 1s) in terms of Hamming distance.

The first method was evaluated for its simplicity and ease of implementation. The second was designed to force the network to make the internal representations of patterns which are to be associated with the same output value as similar as possible to each other and the internal representations of patterns which are to be associated with different output values as different as possible to each other. This should have the effect of improving the ability of the network to differentiate between separate classes, and generalise between members of the same class.

Network simulations: Computer simulations of PLN and GSN networks were carried out using the two nonrandom learning approaches presented above to test the generalisation ability of the different networks. Each network consisted of eight pyramids of four levels each, with a neuron connectivity of 4. The resulting input space of the networks was 256 bits, arranged as a 16×16 grid of binary values. The training data consisted of eight, 16×16 character patterns, each with a Hamming distance of 48 bits from all of the other patterns. The networks were trained such that each of the eight pyramids was to respond with a 1 for its respective character, and 0 for all the other characters.

The recognition capability of each of the networks was tested by corrupting (i.e. logically inverting) n bits of the first character pattern in random positions, where n ranged from 0 to 49. For each value of n, 1000 randomly corrupted patterns were sequentially applied to the input of the network. Because the input pattern was a corrupted version of the first pattern, only the first pyramid should have responded with a 1. All other network outputs were considered to be erroneous. The number of erroneous outputs per 1000 input patterns was recorded as the error rate for the particular level of corruption.

This test was designed solely as a means of comparing the different neural networks. The types of corruption encountered in real applications, such as blurring, interference or aliasing, may have significantly different characteristics to the random corruption used in this test.

Fig. 1 shows the results of the simulations as a graph of the recognition error rate as a percentage (out of 1000) against the level of corruption as a percentage (of 256 bits).

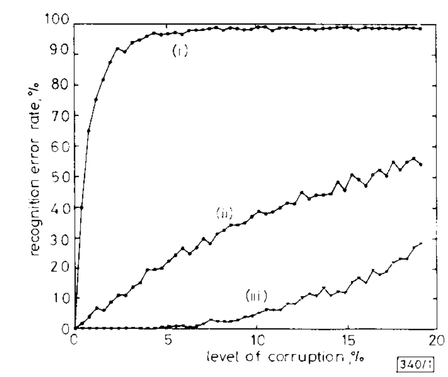

Fig. 1 *Results of recognition capability test*
(i) probabilistic logical neuron
(ii) goal seeking neuron (1)
(iii) goal seeking neuron (2)

Fig. 1 demonstrates the poor generalisation abilities of the PLN network. Even for corruption levels of only 0·8% (the third point), the output of the network is incorrect more than half the time. This means that for applications involving even small differences between the input pattern and the training pattern, the PLN network is unsuitable.

The GSN network using the first nonrandom learning method has substantially better recognition capabilities, only reaching an error rate of 50% with a corruption level of 15%. Most real applications, however, would require much lower error rates, less than 1% for example. The GSN network using the first nonrandom learning method does not meet such a requirement for any level of corruption other than zero.

The GSN network using the second learning technique performed significantly better again than the previous GSN network. At no level of corruption did the error rate rise above 50%, and for corruption levels up to 6%, the error rate remained below 1%.

The GSN network using the original random learning method could have produced either of the above two responses, so it follows that it could also produce a response anywhere in the region bounded by the two GSN responses in Fig. 1, and possibly outside of this region as well. A major feature of the second nonrandom learning method is that it produces a trained network with a consistently good generalisation ability and in a single training pass.

Conclusions: RAM-based neural networks exhibit greater ease of VLSI implementation and faster training than analogue networks, but do not all possess useful generalisation abilities. The PLN has practically no generalisation ability, whereas the original specification of the GSN has a randomly varying capability. A modified training algorithm for GSN networks has been presented which demonstrates consistently good performance, in terms of its recognition capabilities when the input data are corrupted by noise.

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EXCESS LOSS IN SINGLEMODE RIGHT-ANGLE X JUNCTIONS

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Indexing terms: Waveguides, Losses

The excess loss in a right-angle X junction composed of weakly-guiding singlemode buried channel waveguides is quantified numerically and shown to be consistent with a simple physical model based on a Gaussian approximation to the fundamental mode and Fresnel diffraction across the junction.

Introduction: Propagation losses in singlemode buried channel waveguides (BCWs) have now been reduced to such low values, typically 0·025 dB/cm [1], that the excess loss in devices incorporated into BCW circuits should be designed so as not to contribute significantly to the overall loss. One such device that has recently been fabricated is a right-angle X junction with two identical BCWs intersecting at 90° [2].

This junction allows the design of long lengths of BCW within a given area by incorporating a spiral with many loops and an exit for the BCW which crosses the spiral in its plane at right angles. It is claimed that for the particular parameters involved, the excess loss of these junctions is zero [2]. The purpose of this Letter is to quantify the loss numerically and derive an approximate analytical formula based on a simple physical model. It is found that the excess loss, although small, is nonzero.

Physical model: Consider the step-profile right-rangle X-junction shown in Fig. 1 with cores of square cross-section and width 2ρ, core index n_{co} and an infinite cladding with index n_{cl}. Weak guidance is assumed so that $n_{co} \simeq n_{cl}$ and the fundamental mode in the input arm 1 has a scalar description. When the modal field reaches the junction at AA′, it is no longer confined in the lateral, or x, direction and spreads out over the width of the intersecting BCW due to diffraction. The diffracted beam then partially re-excites the fundamental mode over the cross-section BB′ and the remaining power is lost to radiation.

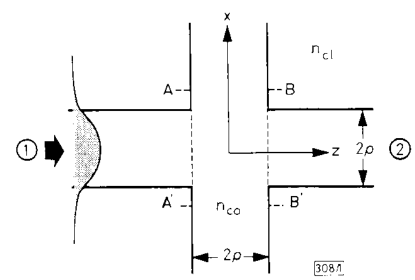

Fig. 1 *Top view of right-angle X junction composed of identical arms*
Core and cladding indices are, respectively, n_{co} and n_{cl}, and core width is 2ρ

To model the physical picture, the fundamental modefield ψ of the square-core guide is approximated by the circularly-symmetric Gaussian field

$$\psi = \exp\left(-\frac{x^2 + y^2}{2s^2}\right) \tag{1}$$

where the spot size s is determined using a standard variational procedure [3]. When the modal field propagates across the region between AA′ and BB′ in Fig. 1, it spreads in both the positive and negative x directions due to diffraction. There is a slight compression in the y direction because the field sees a slab core rather than a square core, but, as the reduction in spot size can be shown to be only of the order of a few percent, it is ignored in the present discussion and the spot size for the y dependence is assumed constant across the junction.

The diffracted field on the cross-section BB′ is calculated by substituting eqn. 1 into the standard expression for Fresnel diffraction in one dimension [4], leading to

$$\psi = \frac{s}{(s^2 - i\sigma^2)^{1/2}} \exp\left\{-\frac{x^2}{2(s^2 - i\sigma^2)} - \frac{y^2}{2s^2}\right\} \tag{2}$$

where $\sigma^2 = \lambda\rho/(\pi n_{co})$ and λ is the source wavelength. Re-excitation occurs at BB′, and the amplitude A of the fundamental mode in arm 2 is obtained from the overlap integral of the diffracted field, eqn. 2, and the Gaussian field in eqn. 1, evaluated over the infinite cross-section and suitably normalised [3]. Accordingly, the fraction of power in arm 1 that re-excites the fundamental mode in arm 2 is given by

$$\frac{kn_{co}s^2}{(k^2n_{co}^2s^4 + \rho^2)^{1/2}} \tag{3}$$