PATTERN SEPARATION IN DIGITAL LEARNING NETS

Indexing terms: Pattern recognition, Networks

Pattern separation is a new technique in digital learning networks which can be used to detect state conflicts. This letter describes pattern separation in a simple single-layer network, and an application of the technique in networks with feedback.

Introduction: The n-tuple method of pattern classification, first proposed by Bledsoe and Browning[1] and implemented in hardware by Aleksander and Albrow,[2] has significant advantages over traditional methods of simple pattern classification.[3] The purpose of this letter is to show how, by using pattern separation in a net with feedback, a pattern associator can be constructed which offers, potentially, very high performance. A thorough introduction to the n-tuple technique of pattern classification is given in Reference 3.

In a normal n-tuple net, k sets of RAMs (or discriminators) are needed to isolate k classes. However, one set can be used to form a simple pattern associator[4] if each class is assigned a class identifier vector (or archetype) $\bar{V}$ of q binary values, where q, the number of n-tuples used to sample the image, is also equal to the size of the image. On a learn cycle, instead of setting the addressed element of the jth RAM, it is given the jth value of its archetype $\bar{V}_j$. The response of the system to an unknown pattern is a Boolean vector $\bar{v}$, representing the class. The Hamming distance (HD) of $\bar{V}$ from $\bar{v}$ is a measure of the difference between the output response vector $\bar{v}$ and the class archetype $\bar{V}$.[5]

One problem with the n-tuple technique is that as different classes and examples are learnt, data stored in the net are overwritten. Pattern separation can detect this and so enable appropriate action to be taken.

Pattern separation: Pattern separation works by considering the response of a RAM to an input to be in one of four states {GND | BLACK | WHITE | UNDEF} instead of a simple Boolean. On system RESET all locations in each RAM are set to the ground {GND} state.

During a learn cycle, if the state $\bar{Q}_j$ stored in the jth RAM at the address defined by a specific n-tuple is {GND}, then the state is changed to that of the desired class vector at the jth position $\bar{V}_j$, {BLACK | WHITE}. However, if $\bar{Q}_j$ has already been defined, and ($\bar{V}_j = \text{NOT}\bar{Q}_j$), then a collision occurs and $\bar{Q}_j$ is set to the undefined state {UNDEF}. The learn cycle is repeated for each of the patterns in the training set {T}.

On analysis, if the state stored in the jth RAM at the address defined by a specific n-tuple is {BLACK | WHITE}, then that value is assigned to the jth element of the output class vector $\bar{v}_j$. Otherwise there is some degree of uncertainty or ambiguity, and so other information is required to define the relevant bit of $\bar{v}_j$. This ambiguity can be resolved by assigning the jth value on the input vector to the jth element of the class vector ($\bar{v}_j := \bar{I}_j$).

This technique forces the class output of the system to reflect that of the input. As long as the archetype is similar to the training set, the output vector will be closer to the archetype than is the case when using a simple pattern associator network.

Pattern separation in feedback systems: In the first proposal of image state feedback in digital learning networks[6] the net is trained to produce a model output vector $\bar{V}$. During use the output vector $\bar{v}$ is fed back and used as the input vector, recognition being defined if the output vector thus produced is stable. Pattern separation can be profitably applied to nets with state feedback by using the different configuration shown in Fig. 1.

The net is trained on a set of images {Td} in various positions using archetype $\bar{D}$, and similarly on another set of images {Ts} for archetype $\bar{S}$. If the initial machine state is $\bar{w}$, after being shown a previously unseen image vector $\bar{I}_d$ of class $\bar{D}$, the net will produce an output vector $\bar{w}'$, a distorted version of the state $\bar{w}$. If the input remains constant at $\bar{I}_d$, the output state will continue to move away from $\bar{w}$ and gradually assume the form $\bar{d}'$ which is close in terms of Hamming distance to $\bar{D}$. Similarly if a previously unseen $\bar{I}_s$ is now presented, the net will eventually converge to a state close to $\bar{S}$.

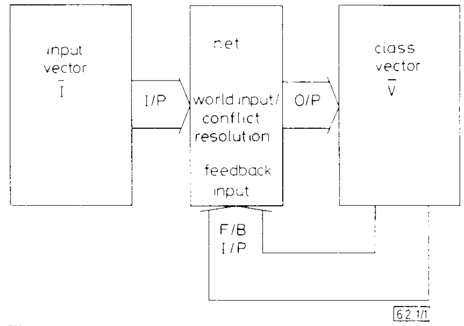

Fig. 1 *Feedback network*

The degree to which a previously unseen image corresponds to previously learnt knowledge is the 'net response'. This is a count of the RAMs which respond unambiguously {BLACK | WHITE}.

When shown a previously unseen image vector I, not from class $\bar{D}$ or $\bar{S}$, the net will output the vector $\bar{\imath}$, close in terms of Hamming distance to $\bar{I}$, since most of the tuple addresses will yield a {GND} state and the output of the jth RAM will thus be a simple copy of the input at the corresponding position $\bar{I}_j$. This state can be detected simply, as the net response will be very low.

Good results have been obtained experimentally using this technique to make a two class decision on images of human faces.

Experiments using pattern separation in feedback nets: The aim of the first experiment was to see if the net output would converge to an image close to the class archetype $\bar{S}$ given a previously unseen member of that class, $\bar{I}_s$, as input.

A net, which was configured with tuple size 8 and input and output vectors of size 64 by 64, was trained on two archetypes $\bar{D}$ and $\bar{S}$ with eight different examples of each. The response of the net to a previously unseen image $\bar{I}_s$ of class $\bar{S}$ is shown in Fig. 2. The archetype, the input and six output states are

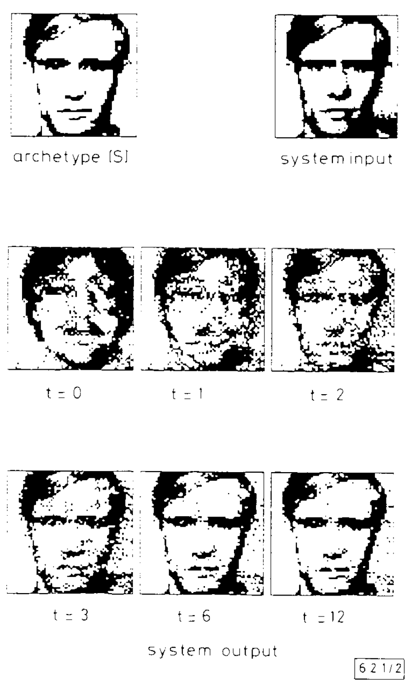

Fig. 2 *System output*

shown, the initial state and after 1, 2, 3, 6 and 12 cycles. The experiment was repeated using a previously unseen image $\bar{I}_d$ from class $\bar{D}$. The Hamming distance of each output vector from its archetype and the net response for each are plotted in Fig. 3.

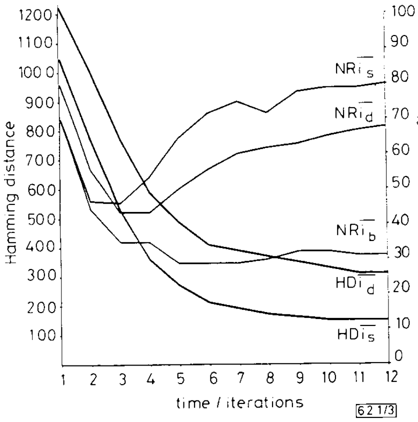

Fig. 3 *Variation in Hamming distance and net response for three subjects*

Init HD$\bar{i}_d$ = 800, init HD$\bar{i}_s$ = 600

The Hamming distance of the final image $\bar{i}_{s12}$ from $\bar{S}$ is 162, compared with an initial distance of $\bar{I}_s$ from $\bar{S}$ of 600. At $t = 12$ the net response is 80%: the system has converged onto the class archetype $\bar{S}$. Similarly the system converged onto class archetype $\bar{D}$ when given a previously unseen input $\bar{I}_d$.

When the net was shown a new image $\bar{I}_b$ from a class $\bar{B}$ it had not been taught, the system entered a state with a net response of 29% indicating that an example of this class had not been seen before. This is also plotted in Fig. 3.

Conclusion: It can be concluded that by preserving information that is lost in a simple network, pattern separation enables a net with feedback to converge to a state very near to the class archetype given a member of that class as input. Copying data from the input vector when a tuple state is ambiguous improves the output pattern response (provided that the Hamming distance between the pattern class archetype and the patterns with which it is associated is small).

Further research is ongoing into multilayer networks using pattern separation, with the aim of enabling a net to converge fully onto a class archetype given a previously unseen member of that class as input.

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TUNABLE TWO-SEGMENT DISTRIBUTED FEEDBACK LASERS

Indexing terms: Semiconductor lasers, Optical communications

We describe a two-segment distributed feedback laser at 1·3 μm with a tuning range of 12·8 Å (209 GHz) and an FM response of 7 GHz/mA. The observed tuning behaviour is in qualitative agreement with an earlier theoretical model. Such two-segment DFB lasers are useful in frequency-multiplexed, frequency-modulated optical networks.

Tunable semiconductor lasers[1] are essential for a number of optical communication systems, such as frequency division multiplexed (FDM) local area networks.[2] In addition, fast and efficient frequency modulation (FM) response is required for FSK operation. In this letter we demonstrate a two-segment distributed feedback (DFB) laser at 1·3 μm that provides a large continuous tuning range (> 200 GHz), high FM efficiency (7 GHz/mA), and a high potential modulation rate. First direct comparison of the measured and calculated tuning behaviour in these lasers shows good qualitative agreement.

Multisegment DFB lasers can provide a significant tuning range[3] and, at the same time, fast FM response.[4,5] A tuning range as large as 24 Å (297 GHz at the 1·55 μm wavelength) has been observed in this laser structure.[3] Flat FM response up to several hundred megahertz has already been demonstrated.[4,5] The potential FM rate of such lasers should be comparable to the intensity modulation rate of high-speed lasers (> 10 GHz). On the other hand, FM response of tunable DBR lasers[1,6] is at present severely limited by the long carrier lifetime of the passive waveguide regions, making them unsuitable for high-speed operation.

We have fabricated two-segment DFB lasers using the semi-insulating-blocked planar buried heterostructure.[7] Strong electrical isolation between the two electrodes (greater than 7·6 kΩ) has been achieved by He ion bombardment in the 30 μm long electrode gap. Light output is measured from the front facet; an unpumped absorbing section between the back electrode and the rear facet suppresses rear facet reflection. The front and back electrodes are 60 and 90 μm long, respectively. Saturable absorption in the unpumped electrode gap region causes bistability of the light against current characteristics. All measurements have been done with the laser in the excited state of the bistable characteristic.

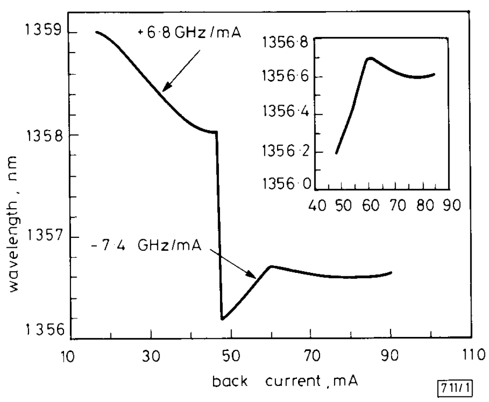

Fig. 1 *Wavelength tuning by back segment current*

I_{front} = 80 mA = constant

Fig. 1 shows wavelength tuning by the back-segment current; the front segment is held at a fixed bias. Two continuous tuning ranges are found with a mode jump between them; the wavelength shift can be either positive (red) or negative (blue). Tuning efficiency is very high; it is +6·8 GHz/mA in the upper mode and −7·4 GHz/mA in the lower mode. The inset in Fig. 1 clearly shows the direction reversal from red to blue of the wavelength shift for the lower mode. Such tuning reversal has been observed previously.[8] Large tuning efficiency and the sign reversals of the wavelength shift clearly demon-