Conclusion: Injection-locked arrays working at 4GHz and showing good radiation patterns have been realised. CPW lines are used to fabricate the oscillator part of the antenna and microtrip lines to built the injection circuit. As each side of the substrate is used for different purposes, the design procedure and the fabrication are simplified. The use of switches is proposed to extend the control of radiated phase to 360° for full beam scanning. This type of antenna could find application as transmitting sources or as Doppler transmit-receive modules.

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References

1 CHANG, K., HUMMER, K.A., and KLEIN, J.L.: 'Experiments on injection locking of active antenna elements for active phased arrays and spatial power combiners', *IEEE Trans.*, 1989, **MTT-37**, (7), pp. 1078–1084
2 FORMA, G., and LAHEURTE, J.M.: 'CPW-fed oscillating microstrip antennas', *Electron. Lett.*, 1996, **32**, (2), pp. 85–86
3 GOUKER, M.: 'Toward standard figures-of-merit for spatial and quasi-optical power-combined arrays', *IEEE Trans.*, 1995, **MTT-43**, (7), pp. 1614–1617
4 HALL, P.S., and HASKINS, P.M.: 'Microstrip active patch array with beam scanning', *Electron. Lett.*, 1992, **28**, (22), pp. 2056–2057

Configuring RBF neural networks

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A novel method (based on the characteristics of scatter matrices and frequency-sensitive competitive learning) for training the hidden layer of a radial basis function neural network is proposed. The method is demonstrated to be robust and to outperform the state-of-the-art algorithm.

Introduction: Owing to their structural simplicity, radial basis function (RBF) networks [1, 2] have been applied to many areas such as image processing, speech recognition and adaptive equalisation. The key issue in configuring an RBF network is the determination of the number and centres of the hidden units. Existing training methods such as competitive learning (CL), frequency-sensitive competitive learning (FSCL) [3] and rival penalised competitive learning (RPCL) [4] suffer from their respective inadequacies. Though FSCL alleviates the sensitivity of CL to the initialisation of the centres of the hidden units, it requires prior knowledge of the number of clusters. RPCL improves upon FSCL by creating a 'rival penalising force', but it suffers severe performance degradation when the number of initial hidden units is less than the actual number of data clusters.

A new approach, called scatter-based clustering (SBC), is proposed to train the hidden layer of the RBF networks. Parameters of scatter matrices are utilised in conjunction with FSCL to derive both the number and locations of the centres. SBC is simple to implement, and is shown to outperform RPCL, the state-of-the-art method.

RBF network: The network consists of three layers; the input, hidden and output layers. An RBF network can be considered as a mapping $F: R^d \to R$ according to

$$F(\mathbf{x}) = w_0 + \sum_{i=1}^{K} w_i \varphi(\|\mathbf{x} - \mathbf{c}_i\|)$$

where K is the total number of RBFs, w_i are the weights of the output layer, $\varphi(\cdot)$ is the basis function and $\mathbf{c}_i$ are the centres of the RBFs.

The weights of the output layer can be obtained by using either pseudo-inverse or the least mean square algorithm if the input training set $\mathbf{x}$ and the corresponding desired output are provided. Different basis functions $\varphi(\cdot)$ can be adopted. The most frequently used basis is the Gaussian function.

Algorithm: Using the characteristics of the scatter matrix, a new criterion called 'sphericity', similar to a parameter used for measuring shape [5], is developed. Let $\mathbf{x}_j^{(L)} = [x_{j1}^{(L)} \ldots x_{jd}^{(L)}]^T$ be the jth d-dimensional pattern vector in the Lth cluster. Furthermore, let $\mathbf{m}^{(L)} = [m_1^{(L)} \ldots m_d^{(L)}]^T$ be the d-dimensional mean vector in the Lth cluster, where $m_i^{(L)} = 1/n_L \Sigma_{j=1}^{n_L} x_{ji}^{(L)}$ and n_L is the number of patterns in the Lth cluster. Denote $\mathbf{M} = (1/n)\Sigma_{L=1}^{K} \Sigma_{j=1}^{n_L} \mathbf{x}_j^{(L)}$ as the total mean vector, where $n = \Sigma_{L=1}^{K} n_L$. Then,

Total scatter matrix:

$$S = \sum_{L=1}^{K} \sum_{j=1}^{n_L} (\mathbf{x}_j^{(L)} - \mathbf{M})(\mathbf{x}_j^{(L)} - \mathbf{M})^T$$

Total within scatter matrix:

$$S_W = \sum_{L=1}^{K} \sum_{j=1}^{n_L} (\mathbf{x}_j^{(L)} - \mathbf{m}^{(L)})(\mathbf{x}_j^{(L)} - \mathbf{m}^{(L)})^T$$

Total between scatter matrix:

$$S_B = \sum_{L=1}^{K} n_L (\mathbf{m}^{(L)} - \mathbf{M})(\mathbf{m}^{(L)} - \mathbf{M})^T$$

Sphericity:

$$\gamma[S_W, S_B] = \frac{Tr(S_W)Tr(S_B)}{Tr(S)}$$

The SBC algorithm, which is motivated to overcome the main defect of the FSCL in requiring prior knowledge of the number of data clusters, can be summarised as follows:

(i) Initialise the number of clusters to be two, $k = 2$.
(ii) Compute cluster centres, $\mathbf{c}_i$, $i = 1, 2, \ldots, K$ using FSCL.
(iii) Assign input patterns to their appropriate centres according to

$$\mathbf{x} \in \mathbf{c}_i \quad \text{if} \quad \|\mathbf{x} - \mathbf{c}_i\|^2 \leq \|\mathbf{x} - \mathbf{c}_j\|^2 \quad \forall j \neq i$$

(iv) Compute $\gamma[S_W, S_B]$.
(v) If the 'knee' of the plot of $\gamma[S_W, S_B]$ against K (see Fig. 1) can be located, stop; otherwise, increment K and go to Step (ii).

It was observed through numerous simulations that the optimal number of hidden units of an RBF network corresponds to K where the 'knee' of the $\gamma[S_W, S_B]$ against K plot is located. The 'knee' is where the value of sphericity begins to stabilise. Well clustered data always exhibited such 'knees' in all of our simulations.

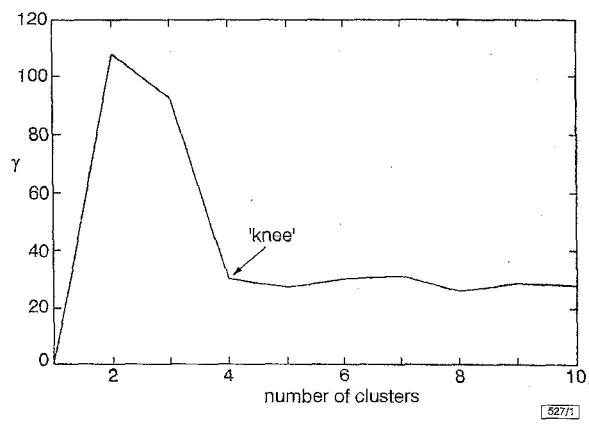

Fig. 1 *Sphericity against number of clusters*

Results: Note that one does not have to guess the initial number of centre units as required by FSCL and RPCL. SBC itself obtains the optimum number and the value of the centre units, thus eliminating the possible performance degradation from inaccurate initialisation of centre units. In contrast, RPCL is sensitive to the learning rate r that produces the rival penalising force, and performs unsatisfactorily when the number of initial centre units are smaller than the actual number of clusters. To compare the performance between SBC and RPCL, an RBF network is utilised to classify the patterns in a 'noisy' XOR problem. The data patterns used for this XOR classification are centred at (–1.0, 0.0), (1.0, 0.0), (0.0, 1.0) and (0.0, –1.0). The deviation is 0.2 with 100 patterns in each cluster. The two clusters centred at (0.0, 1.0) and (0.0, –1.0) form the first class, and the other two clusters centred at (–1.0, 0.0) and (1.0, 0.0) form the second class. The Gaussian function is adopted as the basis function.

Table 1: Classification using RPCL

RPCL parameters	Class	Classified as		Marginally classified as
		Class 1	Class 2	
$r = 0.005$ $k = 5$	Class 1	176	0	24
	Class 2	16	31	153
$r = 0.002$ $k = 5$	Class 1	194	6	0
	Class 2	0	196	4
$r = 0.002$ $k = 3$	Class 1	96	102	2
	Class 2	0	197	3

Table 2: Classification using SBC

Class	Classified as		Marginally classified as
	Class 1	Class 2	
Class 1	197	0	3
Class 2	0	164	6

To examine RPCL on training the hidden layer of the RBF network, where one normally does not know the actual number of data clusters, the number of initial centre units is set as five and $r = 0.005$. The RBF network with these parameters shows a low recognition rate $\simeq$ 52% as illustrated in Table 1 because the rival penalising force is too strong. Note that marginally classified patterns were also considered misclassified. By trial and error, the optimum value of r is found to be 0.002 at which a recognition rate of 98% is achieved. As shown in Table 1, when the initialised centre units ($k = 3$) are less than the actual number of clusters, the recognition rate becomes 73% because there are not enough RBF units to represent the four data clusters. In contrast, SBC achieves a recognition rate of 98% (Table 2).

Conclusion: The proposed SBC algorithm is able to overcome problems encountered in various adaptive competitive learning algorithms in configuring RBF networks.

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References

1 BROOMHEAD, D.S., and LOWE, D.: 'Multivariable functional interpolation and adaptive networks', *Complex Syst.*, 1988, **2**, pp. 321–355

2 MOODY, J.E., and DARKEN, C.J.: 'Fast learning in networks of locally tuned processing units', *Neural Comput.*, 1989, **1**, pp. 281–294

3 AHALT, S.C., KRISHNAMURTY, A.K., CHEN, P., and MELTON, D.E.: 'Competitive learning algorithms for vector quantization', *Neural Netw.*, 1990, **3**, pp. 277–291

4 XU, L., KRZYZAK, A., and OJA, E.: 'Rival penalized competitive learning for clustering analysis, RBF net, and curve detection', *IEEE Trans. Neural Netw.*, 1993, **NN-4**, (4), pp. 636–649

5 ANSARI, N., and DELP, E.J.: 'On the distribution of a deforming triangle', *Pattern Recognit.*, 1990, **23**, (12), pp. 1333–1341

Dispersion penalties in an analogue link operating near 1.3μm

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The authors investigate dispersion penalties in an analogue link using an uncooled Fabry-Perot laser operating near 1.3μm. Mode-partition noise, caused by mode fluctuations combined with dispersion, can rise significantly as the laser temperature rises and, therefore, its wavelength drifts. It is found that in a link transmitting signals near 1GHz the noise may rise by over 20dB, even though the laser wavelength is close to the dispersion zero of the fibre.

Introduction: The low cost of uncooled Fabry-Perot lasers opens opportunities for many new applications, such as transmitting signals originating in homes to the headend of a cable television network [1 – 3], or transporting wireless telephony signals between small, neighbourhood antennas and a centralised base station [4, 5]. In both of these cases the optical link may use an analogue subcarrier to transmit digital signals. Since these lasers are not temperature-controlled, they must operate over a wide temperature range. In this Letter, we investigate how dispersion affects the performance of an analogue optical link as the laser wavelength varies with temperature. We have measured the relative intensity noise (RIN) of an optical link while varying the laser temperature, and the optical modulation depth (OMD) and frequency of a subcarrier.

As a Fabry-Perot laser is modulated, its mode distribution changes. Although the total output power may be a nearly linear function of the drive current, the fraction of power in any one mode will vary. After the light is transmitted through fibre, any fibre dispersion will cause the light from the various modes to arrive at different times, so that the variation in the optical spectrum causes intensity noise, known as mode-partition noise. This phenomenon has been well-studied in digital optical links [6]. In our work we focus on analogue transmission. In an analogue link the low-frequency mode-partition noise will be upconverted by the modulating signal, enhancing the noise within the signal's band.

Previous work on mode-partition noise in analogue optical links has focused on transmission of analogue video signals using temperature controlled lasers [7 – 9]. Meslener [8] concluded that the temperature of a Fabry-Perot laser must be carefully controlled if it is to be used to transmit analogue video signals. However, the carrier-to-noise ratio (CNR) requirements for transmission of digital signals on analogue subcarriers are much lower than those for analogue video signals. In this Letter, we present data on how the noise of an analogue optical link varies over a wide temperature range.

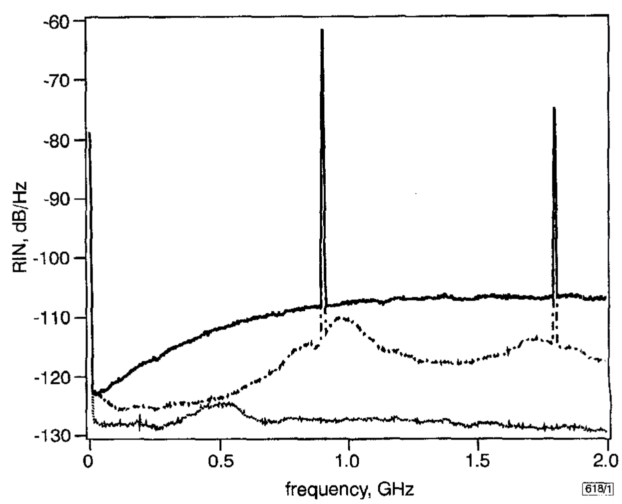

Fig. 1 *RIN against RF frequency*

OMD (900MHz)
··········· 0%
—·—·— 83%
——— 130%

Experiment: A commercial 1.3μm multiquantum-well (MQW) Fabry-Perot laser was used. The laser package did not include a thermo-electric cooler, so the laser temperature was varied by placing the device in a temperature controlled chamber. The temperature was monitored using a thermistor located adjacent to the laser package. The laser was prebiased to an average output power of 2mW. It was modulated with a sine wave, using frequencies varying from 450MHz to 1.8GHz. The OMD was varied from 0% (no modulation) to 130% (we measure the OMD at the modulating frequency, neglecting the harmonic distortion caused by clipping the signal). An optical isolator was used to insure that we were observing noise due to dispersion, rather than noise due to optical feedback. The light was then transmitted through an optical coupler, which diverted 10% of the light to an optical spectrum analyser (OSA). The remaining light was transmitted through 18km of standard fibre, to an RF spectrum analyser.