

Fig. 3 Implementation solutions details for uniplanar couplers

a All four ports fed with coplanar lines b H- and output ports fed in coplanar lines and E-port fed in slotline

Experimental results: Microstrip couplers reported in [1-3] are particular cases of eqn. 1. Two cases of uniplanar couplers are important in practice: (see Fig. 3a and b). In Fig. 3a and b layout solutions for both of the two cases are shown. A case a uniplanar coupler designed using the method presented here was proposed by us [4]. In Table 1 the measured performances of a case b coplanar coupler having  $\theta = 53^{\circ}$ ,  $Z_c = 43\Omega$  are resumed. A radial slotline stub transition has been designed at the E-port in order to test the circuit. The transition affected the measured return loss and transmission when fed to the E-port. A 1.75:1 bandwidth is achieved with a coupler circumference of only  $0.57\lambda_r$ .

Table 1: b-type coupler measured performances in frequency range 3.9-6.8GHz

Parameter	Electrical definition	Measured value
H-port return loss	mag(S <sub>HH</sub> )	<-10dB
Transmission when fed to H-port	$mag(S_{1H}), mag S_{2H})$	$4.5 \pm 0.5 \mathrm{dB}$
Output magnitude balance when fed to H-port	$\operatorname{mag}(S_{1H}/S_{2H})$	$0.0 \pm 0.2$ dB
Output phase when fed to H-port	$phase(S_{1H}/S_{2H})$	0° ± 2°
Output magnitude balance when fed to E-port	$\max(S_{1E}/S_{2E})$	$0.1 \pm 0.3$ dB
Output phase when fed to E-port	phase( $S_{1E}/S_{2E}$ )	180° ± 2°
Isolation	$mag(S_{EH}), mag(S_{12})$	<-22dB

Conclusion: The general theory of 180° hybrid ring couplers is for the first time presented and complete design formulas are given. It is shown that best performances are achieved using uniplanar lines. A design methodology is given. It is shown both theoretically and experimentally that both a small size and a wide bandwidth can be achieved, leading therefore to coupler designs suitable for MMIC integration.

Acknowledgment: The authors thank A. Boulouard from CNET Lannion for his helpful suggestions.

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10 February 1994

Electronics Letters Online No: 19940415

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## Complex-valued neural network for direction of arrival estimation

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Indexing terms: Neural networks, Radio direction-finding

A complex-valued neural network for the implementation of a direction of arrival (DoA) estimator is presented. The network is based on the linear prediction method, with data processed fully in the complex domain. Simulation results are given to demonstrate the effectiveness of the network performances.

Introduction: The direction of arrival (DoA) estimation is one of the important applications in array signal processing. The problem can be solved by the maximum likelihood or linear prediction (LP) methods [1], or the eigenspace method [2]. All of these methods require time-consuming matrix computations.

A neural network, which comprises parallel and highly interconnected simple analogue processing units (neurons), is capable of fast processing with massive parallelism and has a simple VLSI implementation. Jha and Durrani [3] applied the Hopfield model to find the bearing directions of the sources by minimising a mean square error cost function. However, [1] showed that the DoA estimation is actually a complex-valued optimisation problem which cannot be solved by the traditional Hopfield model. We propose alternatively a neural network for DoA estimation by employing the Hirose complex-valued neural network [4] to solve this complex-valued optimisation problem. The network is based on the linear prediction method, with data processed fully in the complex domain. The procedures and circuit dynamics of the neural network will be described in following Sections.

Formulation: Considering a linear array with L elements, the problem of linear prediction for DoA estimation can be formulated as [1]

$$\begin{aligned} & \min_{w} \mathbf{W}^H \mathbf{R} \mathbf{W} \\ & \text{subject to } \mathbf{W}^H \mathbf{E}_r = 1 \end{aligned} \tag{1}$$

where R is the array correlation matrix, W is the solution complex weight vector, E, is the constant vector where its rth element equals 1 and all others equal 0. The superscript 'H' denotes the Hermitian operator. We assume that the weights are phase-only, i.e.  $w_i = exp(j\beta_i)$  where  $\beta_{bi} \in [-\pi,\pi]$  form the outputs of the neural network. The neural network implementation, which leads to the solution of eqn. 1, is summarised as follows:

Step 1: The rth phase argument  $\beta$ , is set to be zero. Thus the linear constraints are always satisfied.

Step 2: Calculate the magnitude  $r_i$  and the phase  $\alpha_i$  of the weighted sum of the inputs fed from all neurons to the ith neuron at time instant t, i.e.

$$r_i(t) \equiv \left| \sum_k R_{ik} w_k(t) \right|$$
 (2)

$$\alpha_i(t) \equiv \arg \left[ \sum_k R_{ik} w_k(t) \right]_{\left(\frac{2\pi}{N_a}\right)} \qquad \alpha_i \in [0, 2\pi)$$
 (3)

where  $N_a = 2^{ma}$ , ma is the number of bits used to represent each of the phase variables'  $\alpha_i s$ . [] $(2\pi N_i)$  denotes the value nearest to one of the discrete values  $k(2\pi/N_a)$ ,  $0 \le k < N_a$  where k is an integer.

Step 3: Let the circuit dynamic equation be

$$C_{i}\frac{d\beta_{i}(t)}{dt} = -r_{i}(t)\sin[\alpha_{i}(t) - \beta_{i}(t)] \tag{4}$$

where  $C_i > 0$ ,  $\beta_i(t) = \{\beta_i(t)\}_{i \ge N_b}$ ,  $N_b = 2^{mb}$  and mb is the number of resolution bits used for the phase argument of the weights.  $\{\cdot\}_{i \ge N_b}$ denotes the value nearest to one of the discrete values  $k(2\pi/N_b)$ ,  $(NJ2) \le k \le (NJ2).$ 

Step 4: Repeat steps 2-3 until equilibrium is reached.

To see that the network as described actually leads to the solution of eqn. 1, we define an energy function E to be the real part of the cost function W"RW, which, in fact, is the cost function itself because R is Hermitian; then from eqns. 2-4 we have

$$\frac{dE}{dt} = \frac{d}{dt} \operatorname{Re}[\mathbf{W}^H \mathbf{R} \mathbf{W}]$$

$$= 2\operatorname{Re}\left[\frac{d\mathbf{W}^H}{dt} \mathbf{R} \mathbf{W}\right]$$

$$= -2 \sum_{i} C_i \left(\frac{d\beta_i}{dt}\right)^2 \le 0$$
(5)

As a result, the energy function decreases monotonically and terminates eventually when the phase arguments' \(\beta\_i s\), reach the equilibrium point.

Simulation results: A 10 element linear array with half wavelength spacing is used as an example to demonstrate the effectiveness of the network performances. The variance of the white noise present in each element is assumed to be 0.1. It is assumed that there are two signal sources impinging from the directions of 75 and 80° with respect to the array, and the signal to noise ratios for both cases are 20dB. The simulation is performed by the fourth-order Runge-Kutta method. The parameters used in the simulation are:  $C_i = 5 \text{pF}$  for all i, ma = 12, and time step size =  $10^{-13}$  s.

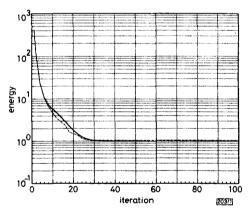


Fig. 1 Time evolution of energy function for neural network DoA esti-

In this example, 8bit, 12bit, and 15bit phase resolutions are employed. Fig. 1 shows the transient response of the output energy function for the three cases. It is noted that the convergence time of each curve and their convergence values are only slightly affected by the phase resolution. Fig. 2 shows the spatial

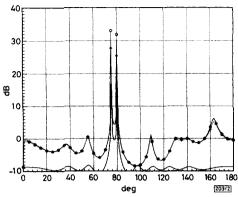


Fig. 2 Resulting spatial spectrum of different phase resolution conditions

· Δ · · 12 bit · + · · 8 bit

spectra of the resulting array responses corresponding to three cases. The spatial spectrum is defined as the inverse of the array voltage response, i.e.

$$P(\theta) = \frac{1}{|\mathbf{W}^H \mathbf{a}(\theta)|} \tag{6}$$

where  $\mathbf{a}(\theta)$  is the steering vector of the array. Apparently, higher phase resolution results in higher spectral peaks located at the directions of signals, as desired.

The theoretical spectrum estimate for the optimal weights is [1]

$$P_{LP}(\theta) = \frac{1}{|\mathbf{E}_r^T \mathbf{R}^{-1} \mathbf{a}(\theta)|}$$
 (7)

which is also shown in Fig. 1 for comparison.

Conclusions: A fully complex-valued neural network for narrowband DoA estimation with phase-only weights is proposed. The processing time is greatly reduced so that the network can update the array weights very rapidly to accommodate any new arriving signals. Simulation results are given to demonstrate the effectiveness of the network performances.

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