deteriorates for levels that are more than 50 dB below the maximum, which will be close or even below the noise floor level, when carrying out measurements.

Table 1: Source distributions analysed

	EMC	Amplitude	Phase (deg)
Case 1	M_x	$0.0025+x'^2+y'^2$	0.0
	M_y	$0.25/(0.25+x'^2+y'^2)$	$180\sqrt{(x'^2+y'^2)}$
Case 2	M_x	$e^{-128(x'^2+y'^2)}$	0.0
	M_y	0.0	0.0

Regarding the MGA optimisation procedure, Fig. 5 shows for case 1, as a representative example, the variation in fitness value, as given by (4), against the number of iterations. Two important observations can be made from Fig. 5: (i) the MGA restarts the population when the lack of diversity among the potential solutions makes the optimisation process stagnate, as can be seen from the sudden dips in the average fitness value; and (ii) the best value of the fitness (which is not necessarily the global maximum, but satisfies our requirements for future real measurements), is reached by the 340th generation. Far more iterations, at the expense of a higher CPU time, should be performed for source reconstruction purposes, so that current densities can be arranged thoroughly.

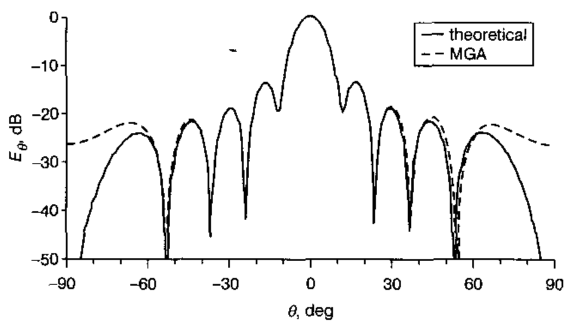

Fig. 2 *Far-field pattern for $\phi = 0°$ cut in case 1*

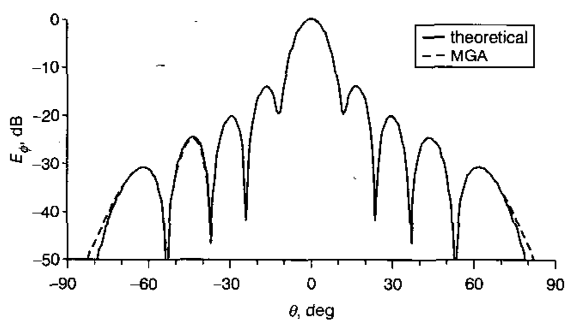

Fig. 3 *Far-field pattern for $\phi = 90°$ cut in case 1*

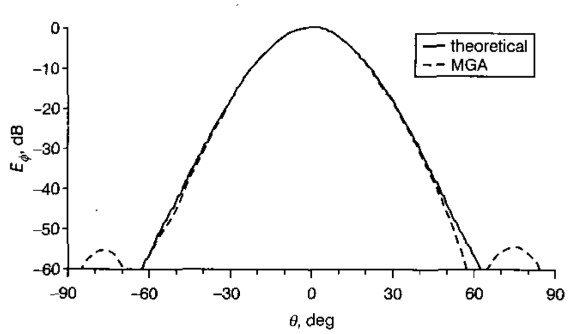

Fig. 4 *Far-field pattern for $\phi = 0°$ cut in case 2*

Conclusions: A NF-FF transformation technique for planar scanning based on an EMC representation of the radiating source, using MGA as the solving method, has been presented. MGA have proved to obtain optimal solutions, as can be inferred from the numerical far-field results shown. Numerical noise, and the binary nature of the MGA makes it difficult to fit the radiation patterns for levels 50 dB below the maximum, although this is certainly enough for real measurement setups. The integral formulation, and the whole method itself, can be easily modified to be applied to cylindrical or spherical acquisition, although for these scanning techniques the complexity increases, because there are not decoupled expressions to link the current densities and the near-field samples.

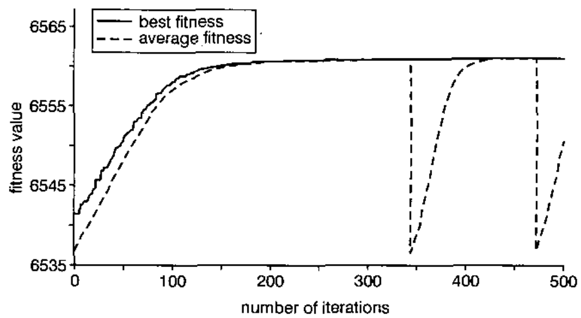

Fig. 5 *Fitness evolution for case 1*

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Effective beamformer for coherent signal reception

Linrang Zhang, H.C. So, Li Ping and Guisheng Liao

A new two-stage beamformer for coherent signal reception is proposed. The first stage extracts all the coherent signals from an antenna array using their direction-of-arrival information, and then the resultant signals are coherently combined in the second stage. Simulation results are included to demonstrate the effectiveness of the proposed technique.

Introduction: It is well known [1] that the performance of a conventional optimum beamformer, which assumes a single signal source, degrades in the presence of multiple coherent sources. Typical coherent signal reception methods to resolve this problem include averaging techniques in the spatial or frequency domains to remove the coherent components prior to beamforming. After decorrelating the coherent signals, the beamformer can put nulls in their directions-of-arrival (DOAs).

However, in many scenarios such as multipath propagation, steering the nulls in the directions of the coherent signals is not desirable. To fully utilise the information of the coherent signals, a potentially more efficient strategy is combining these signals constructively instead of cancelling all but one of them. A number of blind beamformers, which make use of the desired signal properties, such as the cumulant [2] and cyclostationary [3] approaches, have been proposed to achieve better performance. However, these methods are generally difficult to implement and need a large number of snapshots for convergence. A multiple constrained method has also been suggested in [4] by using high-order null constraints in the DOAs associated with the coherent signals in order to prevent signal cancellation. Since this algorithm does not exploit the energy of all coherent signals, optimum performance cannot be achieved. In this Letter, an improvement to [4] for efficient coherent signal reception is devised.

Problem formulation: Assume that plane waves emitted by a desired group of P coherent sources and J uncorrelated interferences impinge on an M-element antenna array from distinct directions θ_{di}, $i = 1, 2, \ldots, P$ and θ_{ui}, $i = 1, 2, \ldots, J$, respectively. These sources are assumed to be narrowband with the same centre frequency and in the far field of the array. The received array signal vector can be expressed as

$$\mathbf{x}(t) = s_d(t)\sum_{i=1}^{P}\alpha_i\mathbf{a}(\theta_{di}) + \sum_{i=1}^{J}s_i(t)\mathbf{a}(\theta_{ui}) + \mathbf{n}(t) \qquad (1)$$

where $s_d(t)$ represents the desired signal waveform, and $s_i(t)$ represents the ith interference waveform, $i = 1, 2, \ldots, J$. The quantity α_i represents the unknown complex amplitude of the ith coherent signal, the $M \times 1$ vector $\mathbf{a}(\theta)$ is called the steering vector of the array, and $\mathbf{n}(t)$ is the spatially white noise vector. It is assumed that $s_d(t)$, $\{s_i(t)\}$, and $\mathbf{n}(t)$ are uncorrelated with each other, and the DOA information of the coherent signals is available or has already been accurately estimated [1]. Denote the composite vector associated with the coherent sources as

$$\tilde{\mathbf{a}} = \sum_{i=1}^{P}\alpha_i\mathbf{a}(\theta_{di}) = \mathbf{A}\cdot\boldsymbol{\alpha} \qquad (2)$$

where $\mathbf{A} = [\mathbf{a}(\theta_{d1}), \mathbf{a}(\theta_{d2}), \ldots, \mathbf{a}(\theta_{dP})]$ and $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_P]^T$, which is also referred to as the generalised array manifold [2] of the desired signal. Given $\mathbf{x}(t)$ and $\mathbf{A}$, the task is to devise an efficient beamforming weight vector.

New beamformer development: If the waveform of the desired signal is known, i.e. when a training signal is available, the optimum weight vector $\mathbf{W}$ for processing $\mathbf{x}(t)$ can be computed by minimising the mean square error function $E\{|s_d(t) - \mathbf{W}^H\cdot\mathbf{x}(t)|^2\}$, where $(\cdot)^H$ denotes conjugate transposition. The minimum mean square error (MMSE) solution is given by

$$\mathbf{W}_{MMSE} = \mathbf{R}_{xx}^{-1}\mathbf{r}_{xs} \qquad (3)$$

where $\mathbf{r}_{xs} = \mathrm{E}\{\mathbf{x}(t)\cdot s_d^*(t)\}$, $(\cdot)^*$ is the conjugate operation, and $\mathbf{R}_{xx} = E\{\mathbf{x}(t)\mathbf{x}(t)^H\}$ is the correlation matrix of the array vector. In the MMSE beamformer, the multiple correlated wavefronts corresponding to the coherent signals are optimally combined to maximise the output signal-to-noise ratio (SNR). However, using a training signal implies an overheard of bandwidth expansion and it may not be preferred in many practical situations. In the following, a new blind beamformer, which requires no training signals, is developed.

We first use the DOA information of the coherent signals to construct multiple constraints for the minimum variance beamformer, such that the coherent signals are preserved and signal cancellation is avoided. This multiple constrained minimum variance (MCMV) beamformer is determined from the following constrained optimisation problem [4]

$$\mathbf{W}_{MCMV} = \arg\min_{\mathbf{W}} E\{|\mathbf{W}^H\cdot\mathbf{x}(t)|^2\}, \quad \text{subject to } \mathbf{A}^H\mathbf{W} = \mathbf{f} \qquad (4)$$

where $\mathbf{f}$ is the $p \times 1$ unknown response vector to be determined. It is clear that $\mathbf{f}$ is dependent on $\boldsymbol{\alpha}$. According to adaptive array theory, the optimal weight vector for (4) is given by

$$\mathbf{W}_{MCMV} = \mathbf{R}_{xx}^{-1}\mathbf{A}(\mathbf{A}^H\mathbf{R}_{xx}^{-1}\mathbf{A})^{-1}\mathbf{f} \qquad (5)$$

Note that the choice of the constrained vector $\mathbf{f}$ has a significant effect on the system performance. In [4], $\mathbf{f}$ is chosen as $[1, 0, \ldots, 0]^T$, which corresponds to preserving the signal in only one desired direction and forcing the receiver response at the directions of the remaining $(P-1)$ coherent signals to zero. This method does not make use of the energy in the coherent signal components and, therefore, is not optimal. In [5], $\mathbf{f} = [1, 1, \ldots, 1]$ is suggested to recover all coherent signals. However, this choice of $\mathbf{f}$ can increase noise energy, which results in output signal-to-interference-plus-noise ratio (SINR) reduction. In general, an optimisation procedure can be used to obtain the constrained vector $\mathbf{f}$ but this normally involves excessive computational costs, especially for real-time applications.

We propose to use P constrained vectors that is a generalisation of the method in [4]. All the coherent signals can be extracted one by one from each individual direction without causing signal cancellation. After all the coherent signals have been extracted, we then combine them optimally. As a result, the proposed beamforming approach consists of two stages: first use a set of adaptive beamformers to extract the desired signal along each DOA while suppressing all interferences, then constructively combine the extracted signals to achieve nearly optimum signal estimation. The operating procedure of the proposed blind coherent signal receiver is summarised in the following two steps.

Step 1: Extract the desired signal along each of the DOAs using the generalised MCMV beamformer. The adaptive beamforming weight vector for the lth direction of the desired signal is computed as

$$\hat{\mathbf{W}}_l = \arg\min_{\mathbf{W}_l} E\{|\mathbf{W}_l^H\cdot\mathbf{x}(t)|^2\}, \text{ subject to } \mathbf{A}^H\mathbf{W}_l = [0\cdots1\cdots0]^T \overset{def}{=} \mathbf{1}_l, \quad l = 1, 2, \ldots, P \qquad (6)$$

where $\mathbf{1}_l$ is a vector with all elements equal 0 except 1 at the lth position. The output of the lth filter is given by

$$y_l(t) = \hat{\mathbf{W}}_l^H\cdot\mathbf{x}(t) = \hat{\mathbf{W}}_l^H\cdot s_d(t)\sum_{i=1}^{P}\alpha_i\mathbf{a}(\theta_{di}) + \hat{\mathbf{W}}_l^H\cdot\left[\sum_{i=1}^{J}s_i(t)\mathbf{a}(\theta_{ui}) + \mathbf{n}(t)\right] = \alpha_l s_d(t) + e_l(t) \qquad (7)$$

where $e_l(t)$ denotes the residual noise plus interference after filtering. Clearly, $\hat{\mathbf{W}}_l$ picks up the desired signal along $\mathbf{a}(\theta_{dl})$ without considering the signals along $\mathbf{a}(\theta_{d1}), \ldots, \mathbf{a}(\theta_{d(l-1)}), \mathbf{a}(\theta_{d(l+1)}), \ldots, \mathbf{a}(\theta_{dP})$. As a result, the use of P weight vectors allows us to extract all coherent signals at different directions.

Step 2: Coherently combine the first stage filter outputs to increase the SNR of the final signal estimate. Stacking the filter outputs from all coherent signal directions, $\{y_l(t)\}_{l=1}^{P}$, yields a more compact vector form:

$$\mathbf{y}(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \\ \vdots \\ y_P(t) \end{bmatrix} = \boldsymbol{\alpha}\cdot s_d(t) + \mathbf{e}(t) \qquad (8)$$

Because of interference and noise suppression at the first stage, the total signal power in $\mathbf{y}(t)$ will be significantly higher than that of $\mathbf{e}(t)$. In this case, $\mathbf{R}_{yy} = E[\mathbf{y}(t)\cdot\mathbf{y}(t)^H] = p_s\boldsymbol{\alpha}\cdot\boldsymbol{\alpha}^H + \mathbf{R}_{ee} \simeq p_s\boldsymbol{\alpha}\cdot\boldsymbol{\alpha}^H$, where p_s is the desired signal power. It enables us to approximate the optimum vector using the principal eigenvector of $\mathbf{R}_{yy}$, which can be obtained using standard decomposition techniques. Such an approximation results in a trade-off between optimality and complexity. It is noteworthy that a similar technique has been employed in practical RAKE receivers in communication systems.

Simulation results: Several simulation examples are presented below for illustration and comparison. We consider a uniformly linear array with 16 sensors, i.e. $M = 16$, and the inter-element spacing is equal to the half of the wavelength of the signals. There are four signals impinging on the array from angles of −40°, −20°, 10° and 30°, off the array broadside. The first three signals are assumed to be the desired coherent signals with known DOAs but different unknown gains and the fourth signal is an uncorrelated interference with interference-to-noise ratio of 60 dB.

Example 1: Fig. 1 shows the beam patterns of the MMSE and proposed beamformers when the coherent signals have SNRs of 23, 25, and

20 dB, respectively. We see that the two-stage beamformer can cope with the problem of the coherent signal situation. It produces three main beams with gains proportional to the amplitude of each coherent signal for simultaneous reception of the desired signals, and a null for successful suppression of the interference. Moreover, its performance is comparable with that of the MMSE approach, although the former is a blind processor while the latter requires training signals.

Example 2: Fig. 2 shows the beamformer output SNR against input SNR. We assume that the SNRs of the three coherent signals are $[-\beta, 0, \beta]$dB, and the value of β is varied from 0 to 20. Apart from the MMSE and proposed methods, we also include the performance of the MCMV approach [5] with fixed constraints based on $\mathbf{f} = [1, 1, \ldots, 1]$. The proposed method has performance similar to that of the MMSE algorithm for the whole SNR range, and is superior to the fixed MCMV beamformer, particularly when the SNR difference among the three coherent signals is large.

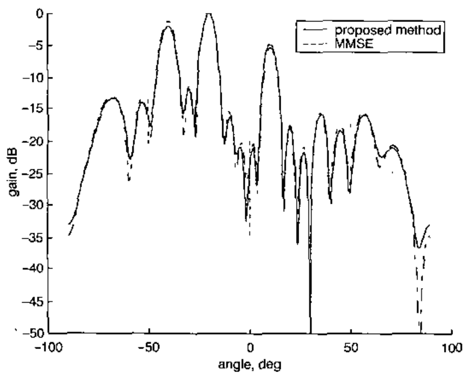

Fig. 1 *Beam pattern*

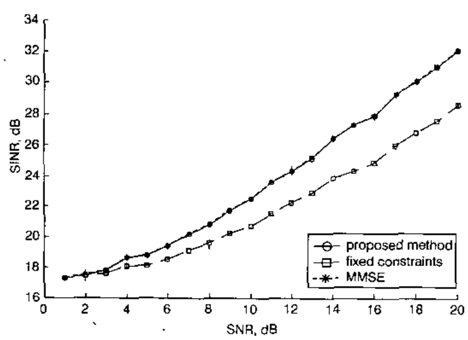

Fig. 2 *Output SINR against SNR*

Conclusion: A two-stage beamformer for coherent signal reception is proposed. The first stage of the proposed beamformer extracts the desired signal along each individual direction of the coherent components, and the second stage combines the outputs of the first stage coherently. Numerical examples show that the proposed beamformer can achieve nearly optimum performance. As a future direction, we will use the eigenstructure of the covariance matrix that constrains the weight vector along the individual direction in the signal subspace [6] to enhance the performance of the proposed approach, in order to cope with performance degradation due to sample covariance errors, DOA estimation errors and other array imperfections.

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Fast efficient method for analysis of insulated wire antennas above ground

Xianshan Li, K. El Khamlichi Drissi and F. Paladian

With an images model for lossy ground and an equivalent polarisation charges model for insulation, a fast efficient method is proposed to solve the problem of insulated wires above ground. The results obtained exhibit excellent agreement with those obtained by rigorous methods of experiment.

Introduction: To develop a fast efficient method for the analysis of insulated wire antennas above a lossy ground, the crucial problems are the insulation modelling, the half-space modelling, and their incorporation into an appropriate numerical method.

Here, the insulating layer is modelled by equivalent polarisation charges, which are related to the free current of the core conductor. The lossy half-space is modelled by equivalent images [1, 2] the currents of which can be expressed in terms of the source current. In this way, the insulation and lossy half-space add no new unknowns to the problem solution. These models are then incorporated into a point-matching moment method [3] to achieve a unified model for bare and insulated wires in free space and above ground. With reasonable approximation, the impedance elements can be reduced to closed form expressions without any integral calculation. Using these, the computation speed is improved enormously compared with conventional methods involving time-consuming volume, surface, or Sommerfeld-type integrations. Typical comparisons are made between the results obtained by the method proposed here and the available results obtained by rigorous methods of experiment.

Bare wire formulation: For a thin-wire antenna in free space (ε_0, μ_0, σ_0), the vector potential $\mathbf{A}$ and the scalar potential Φ produced by the source charge and current on the surface of the wire antenna are obtained as

$$-E_\ell^i = -j\omega A_\ell - \frac{\partial \Phi}{\partial \ell} \qquad (1)$$

where $\mathbf{E}^i$ is the known impressed field, ℓ is the length variable along the wire axis.

We divide the wire axis into N small segments with each one denoted by its starting point n^-, midpoint n, and its termination point n^+. Using the point-matching method [3], (1) can be converted into a matrix equation as

$$[V] = [Z][I] \qquad (2)$$

where V is the known impressed excitations, I is current expansion coefficients. More mathematical treatment is available in [3]. The impedance element is formulated as

$$Z_{mn} = \Psi_A(n, m) + \Psi_\Phi(n, m) \qquad (3)$$