A decision directed smart antenna system with neural estimation for M-quadrature amplitude modulated signals

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Adaptive beamforming and direction of arrival (DOA) estimation are among the prime areas of research which draw the attention of the research community to address the ever growing demand for increased capacity in mobile communication systems. Smart antennas, which are essentially adaptive array antennas coupled with intelligent signal processing have emerged as an important category of systems capable of providing solution to this problem. Neural networks are also being widely used for developing intelligent systems and influencing signal processing in communication systems. A decision directed approach is proposed for blind adaptation of smart antenna system using a complex neural estimation of parameters for beamforming. The paper presents a simulation study of the decision directed smart antenna system with neural estimation (DDSA-NE) for multi-quadrature amplitude modulated (M-QAM) signal environment with 4, 16, and 64 constellations. The results indicate the effectiveness of the proposed scheme.

Keywords: Beamforming, Direction of arrival (DOA), Adaptive array antenna, Neural network, Multilayer perceptron
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1 Introduction

Spectrum efficiency is the most important issue while addressing the challenge of ever growing demand for increased capacity in wireless systems to meet communication traffic in modern age. Various techniques are explored by researchers to utilize the spectrum in the best possible way such as coding and compression, higher-order modulation, adaptive interference management, dynamic spectrum management, and smart antennas. These can be applied independently or jointly. Smart antennas are emerging as a strong tool for addressing interference as well as spectrum management. An antenna array, combined with adaptive signal processing in both space and time domain, is termed as ‘smart antenna’. Primarily, a smart antenna is an adaptive system designed to either distinguish among desired signals, multipath and interfering signals, or estimate direction-of-arrivals (DOA) required for optimum beamforming.

An adaptive antenna system must respond to changes in environment. To achieve this capability, conventional methods require reference signal transmission, e.g. periodic training sequences to extract information about the environment. The well known adaptive algorithms such as: least mean squares (LMS), recursive least squares (RLS) and least squares (LS), etc. may be employed. In case training sequence transmission is not available, the adaptive system has to use a blind algorithm. Blind algorithms, in the absence of reference signal use some property of the desired signal to generate an estimate for adaptation. Important classes of blind algorithms include eigen-based approach, constant modulus approach$^1$, property restoral algorithms$^2$, spectral self-coherence algorithms$^3$ and decision-directed algorithms.

Neural networks are powerful artificial intelligence tools with broad range of applications including communication signal processing, control and trend extraction. They have the capability to learn from the experiences and fit into requirements where system is too complex to be modeled mathematically. They are particularly useful in situations where it is difficult to specify a sequential algorithm or data is highly non-stationary. With increasing applications of neural networks in adaptive signal processing, some neural approaches in designing smart antennas have been reported$^4$-$^8$. The key feature, in any neural based smart antenna, is the mapping provided between the received signal and the antenna's behaviour as a continuous function, which makes it possible to
formulate solutions for diverse problems such as direction finding, source separation, or adaptive beamforming. All schemes involving neural systems have their own merits and limitations if compared on computational complexity, accuracy levels and convergence. So, the applicability of a neural technique mainly depends on the signal processing aspects. Smart antennas are employed for different tasks with different approaches of which certain may be suitable for interference rejection while others for diversity reception and vice versa. It is difficult to design a single smart antenna which is ideal for all tasks and as applicable with any adaptive system. Smart antenna system design is a trade-off between complexity and performance.

Digitally modulated signals are well structured signals and provide an opportunity to develop a property restoral algorithm that exploits prior knowledge of signal format for improved estimation. Designing a smart antenna for digital transmission using a decision directed approach is more attractive as symbol decisions made on a preliminary signal estimate can be used to generate a new set of beamformer weights and further update signal estimates. Thus, iterative method may be used to realize beamformer by projecting the resulting signal estimate onto the nearest symbol.

This paper presents a decision-directed approach for smart antenna for 4, 16 and 64-quadrature amplitude modulated (QAM) signals. The proposed scheme makes use of neural signal processing for implementing a decision directed smart antenna employing a complex estimator.

2 Array steering vector and multi path channel model

The signal observed at the $k$th element of an array due to a plane wave received as shown in Fig. 1 is given by:

$$\tilde{x}_k(t) = G_k(\varphi) \tilde{r}(t + \tau_k) + \tilde{n}_k(t)$$  \hspace{1cm} (1)

where, $\tilde{r}(t)$, is the incident signal; $\tilde{n}_k(t)$, the measured noise for the $k$th antenna; $G_k(\varphi)$, the gain for the $k$th element at angle of arrival (AOA) $\varphi$; and $\tau_k$, time difference of arrival (TDOA). Assuming bandpass signal with slowly varying complex envelope, the narrow band array approximation allows phase shift to be expressed in terms of delay $\Psi_k$. So, received signal $r(t + \tau_k)$ can be expressed as $a_k(\varphi)r(t)$, where, the complex scalar $a_k(\varphi)$, is $G_k(\varphi)e^{j\Psi_k}$. Accordingly, the signal experienced at each element is represented in vector form as:

$$X(t) = \tilde{\alpha}(\varphi)r(t) + \tilde{n}(t)$$  \hspace{1cm} (2)

The steering vector $\tilde{\alpha}(\varphi)$ describes mapping between AOA and array response which is completely defined by array geometry and gain patterns of the individual elements. The steering vector model represented by Eq. (2) applicable to line of sight conditions can be extended to model the received signals with multiple time-delayed signals arriving from $L$ number of paths with a distinct AOA. It is known as specular multipath channel and given by

$$x(t) = \sum_{l=1}^{L} \alpha_l a(\varphi_l) r(t - \tau_l) + n(t)$$  \hspace{1cm} (3)

The effect of all arriving signal vectors is lumped into a single vector quantity, $\tilde{\alpha}(t)$, called spatial signature of $r(t)$. When the path delays are small, the channel is flat fading and the signal $x(t)$ can be approximated as:

$$s(t) = \left(\sum_{l=1}^{L} \alpha_l a(\varphi_l)\right) r(t) \approx \tilde{\alpha}(t)r(t)$$  \hspace{1cm} (4)

3 Blind deconvolution and adaptive beamforming

Deconvolution is a process to recover the signal passed through a filter and can be applied for separating signals. In communication systems, deconvolution is widely used for equalization of channel with unknown characteristics to recover the signal with best estimates. Blind deconvolution aims to estimate the signal-of-interest from the observed signal without knowing the convolving system. In a decision-directed approach, the received signal is assumed to be generated by convolution of transmitted signal with some unknown, causal, linear time-

![Fig. 1—Geometrical description of array and propagation signals](image-url)
invariant (LTI) filtering and deconvolution is applied to retrieve the original source signal as an estimate \( \hat{s}(n) \), by filtering with another causal finite impulse response (FIR) filter. This can be treated as an optimization problem and implemented using LMS gradient adaptation of the filter weights by a chain rule. The cost function in such optimization problems can be obtained using Bussgang property stated as\(^1\):

\[
E\{\hat{s}(n)\hat{s}(n-k)\} = E\{\hat{s}(n)g(\hat{s}(n-k))\} \quad \ldots (5)
\]

Where, \( g(.) \) is a zero-memory nonlinearity chosen appropriately. Algorithms using this property are known as Bussgang algorithms and filter update is obtained by:

\[
w_k(n+1) = w_k(n) - \mu(n) \frac{\partial J(\hat{s}(n))}{\partial w_k} \quad \ldots (6)
\]

\[
= w_k(n) + \mu(n)g(\hat{s}(n))x^*(n-k)
\]

where, \( \mu(n) \) is adaptation step at nth iteration; and \( ^* \) denotes complex conjugation. The function \( g(\hat{s}) \) is chosen appropriately and depends on the statistics of source signal\(^2\). Several good performing Bussgang algorithms are known\(^13-16\), which mainly differ from each other on account of zero-memory nonlinearity function defined differently in each case. The smart antenna working as adaptive beamformer requires a particular choice of \( w(t) \) to produce a gain pattern defined by \( F(\phi) = |w(t)^H \tilde{a}(\phi)|^2 \), where, the vector \( \tilde{a}(\phi) \) is the steering vector of the array. The gain pattern describes the power in the beamformer output due to a signal impinging on the array from a particular AOA, \( \phi \). Extracting channel characteristics from signal impinging on the array requires deconvolution operation for estimating weights adaptively which can result in a desirable array pattern.

4 Decision directed smart antenna with neural estimation (DDSA-NE)

The decision directed approach presented here makes use of a blind algorithm\(^14\) for realizing deconvolution and obtain the weights for antenna array. In the proposed scheme, a complex multi layer perceptron (CMLP) is used to replace the conventional linear FIR filter for the smart antenna to adapt blindly employing decision directed neural estimation. The overall scheme of applying CMLP with complex back propagation (CBP) algorithm to implement a decision directed approach is presented in Fig. 2. The complex activation function used in CMLP is given by:

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**Fig. 2**—Decision directed smart antenna with neural estimator
The choice is due to the multi-saturated output region suitable for QAM signals of any constellation size. The slope parameter \( \alpha \), a positive real constant determines the degree of nonlinearity. The CBP algorithm is implemented by splitting into real and imaginary parts. The decision direction is extended to blind algorithm using the complex back propagation as follows:

\[
f(y_{R \text{ or } I}) = y_{R \text{ or } I} + \alpha \sin(\pi y_{R \text{ or } I}) . \quad \ldots \ (7)
\]

\[
w_{j,R}^{o}(p + 1) = w_{j,R}^{o}(p) + \eta_{1}(\xi_{p,R} e_{p,R}^{o} i_{p,j,R} + \xi_{p,I} e_{p,I}^{o} x_{p,i,l}) \quad \ldots \ (8)
\]

\[
w_{j,I}^{o}(p + 1) = w_{j,I}^{o}(p) - \eta_{1}(\xi_{p,R} e_{p,R}^{o} i_{p,j,I} - \xi_{p,I} e_{p,I}^{o} i_{p,j,I}) \quad \ldots \ (9)
\]

for updating the weights linking output neuron, and

\[
w_{j,R}^{h}(p + 1) = w_{j,R}^{h}(p) + \eta_{2}(\xi_{p,R} e_{p,R}^{h} x_{p,i,R} + \xi_{p,I} e_{p,I}^{h} x_{p,i,l}) \quad \ldots \ (10)
\]

\[
w_{j,I}^{h}(p + 1) = w_{j,I}^{h}(p) - \eta_{2}(\xi_{p,R} e_{p,R}^{h} x_{p,i,l} - \xi_{p,I} e_{p,I}^{h} x_{p,i,l}) \quad \ldots \ (11)
\]

for updating the weights linking the hidden neurons. Here flags \( \xi_{p,R} \text{ and } \xi_{p,I} \) use Sato-like errors and set as 1 or 0 depending on the estimated error. The error estimation has to be different for different values in an M-QAM system and controlled by a real valued parameter \( \beta \) to determine on which intervals of the real and imaginary axes the error on the decided symbol may be used for adaptation. The parameter \( \beta \) is set equal to 1, 3, and 7 for \( M = 4, 16, 64 \), respectively in M-QAM signals according to

\[
\beta = \begin{cases} \sqrt{M} - 1, & \text{for } M = 2^k, \ k = 2,4,6,... \\ \frac{M}{2} - 1, & \text{for } M = 2^{k+1}, \ k = 2,3,4,... \\ \end{cases} \quad \ldots \ (12)
\]

which gives maximum covering of reliable regions for improved decision direction.

The structure of the CMLP is chosen according to size of the array. It contains at least one hidden layer in addition to the input and output layers. Input layer contains nodes equal to number of array elements and output layer contains single node. Relating the size of CMLP with the array length helps the structure to remain small enough to keep computations to minimum and make it compatible physically with the array. The learning rate parameters required in Eqs \([8] \sim [11]\) for hidden layer and output layer are same whereas slope parameter in Eq. (7) for output layer and hidden layer neuron may be chosen differently.

On converging, the decision directed estimation results in desirable set of weights of CMLP. The weights represent the information about the signals arriving at certain angles extracted from the environment in spatial domain. Thus, the features captured from the environment are stored in weights obtained. The weights so achieved can be suitably mapped onto the weight space of the adaptive antenna array system for obtaining the modulus and phase of the coefficients for the desired beamforming. This mapping is obtained by using a simple feedforward network which is continuously trained for set of weights obtained for symbols generated with sufficiently low error. To achieve that, the error is tracked on a moving average basis which is assigned as a threshold of permissible error and for all such errors below the threshold, the corresponding weights are preserved. The feedforward network is trained for set of weights and the direction of arrival. Normally in practical situations also, the array coefficients are calibrated to match the processed signal levels for beamforming. The mapping operation referred is akin to calibration accomplished in weight vector space with equivalent dimensions.

5 Simulation results and discussion

A DDSA-NE as described in Fig. 2 is simulated. Different simulation set-up with two 4, 16, or 64-QAM signals with signal-of-interest arriving at relative difference angle of 15, 30, 45, 60 or 75° at a linear array with isotropic 4, 6, or 8 elements separated by 0.5 \( \lambda \) were considered. This provided a large choice of possible combinations to validate the proposed approach. A Rayleigh fading radio channel and signal-to-noise ratio of 20 dB is assumed.

For a particular case of AOA and array size, several trials were conducted to find the suitable values of learning rate and slope parameters by correlating the error plots with constellation diagrams of processed signal. For a selected set up with the chosen neural parameters, if the estimation of the symbols is in desirable constellation and error of estimation progressively exhibits the convergence, the system can be regarded functioning properly. Decision directed algorithms are inherently susceptible to performing
poorly with wrong initial estimates, the system may fail to capture the convergence quickly. Also, at times, it may be trapped into undesirable constellation state and proceed fast to exhibit false convergence. Therefore, it is essential to correlate the recovered signal constellation and error performance to identify the desired parameters responsible for correct realization of decision directed adaptation. Total eight cases are presented involving various AOA, array size and signal formats as listed in Table 1 along with identified network structures and parameters found suitable. The presented cases involve combination of possible array size and M-QAM system.

Figures (3–5) show the convergence behaviour and corresponding constellations shown for three cases, each for 4, 16, and 64 QAM systems. The phenomenon of decision-direction is observed and constellation diagrams verify that the system achieves satisfactory convergence and symbols progressively approach their designate levels. Figures (6-8) present the beamforming by the DDSA-NE in these cases with the extracted modulus and phase applied to the array. These cases are marked (*) in Table 2.

It can be seen that the adapted beam pattern is able to form the main lobe in the direction very close to the desired beam pattern of the array which it should have.

<table>
<thead>
<tr>
<th>Case</th>
<th>QAM System</th>
<th>Array Size</th>
<th>Network structure</th>
<th>$\mu$</th>
<th>$\alpha_{\text{hidden}}$</th>
<th>$\alpha_{\text{output}}$</th>
<th>$\beta$</th>
<th>Actual AOA</th>
<th>Observed AOA</th>
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<tr>
<td>1</td>
<td>4</td>
<td>4</td>
<td>4-4-1</td>
<td>0.0009</td>
<td>0.7</td>
<td>0.7</td>
<td>1.0</td>
<td>75°</td>
<td>71°</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>6</td>
<td>6-6-1</td>
<td>0.01</td>
<td>0.6</td>
<td>0.6</td>
<td>1.0</td>
<td>15°</td>
<td>18°</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>6</td>
<td>6-6-1</td>
<td>0.01</td>
<td>0.6</td>
<td>0.6</td>
<td>1.0</td>
<td>45°</td>
<td>49°</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>6</td>
<td>6-6-1</td>
<td>0.01</td>
<td>0.6</td>
<td>0.6</td>
<td>1.0</td>
<td>75°</td>
<td>76°</td>
</tr>
<tr>
<td>5</td>
<td>4</td>
<td>8</td>
<td>8-8-6-4-1</td>
<td>0.0001</td>
<td>0.4</td>
<td>0.6</td>
<td>1.0</td>
<td>60°</td>
<td>66°</td>
</tr>
<tr>
<td>6</td>
<td>16</td>
<td>6</td>
<td>6-12-6-1</td>
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<td>0.1</td>
<td>0.1</td>
<td>3.0</td>
<td>45°</td>
<td>44°</td>
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<tr>
<td>7</td>
<td>16</td>
<td>6</td>
<td>6-12-6-1</td>
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<td>0.1</td>
<td>0.1</td>
<td>3.0</td>
<td>75°</td>
<td>68°</td>
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<tr>
<td>8</td>
<td>64</td>
<td>8</td>
<td>8-8-1</td>
<td>0.0005</td>
<td>0.7</td>
<td>0.7</td>
<td>7.0</td>
<td>75°</td>
<td>77°</td>
</tr>
</tbody>
</table>

Fig. 3—Constellation and error plot for 4-QAM 4-Element AOA = 75°; Network structure 4-4-1, $\mu = 0.0009$, $\alpha_{\text{hidden}} = 0.7$, $\alpha_{\text{output}} = 0.7$, $\beta = 1.0$

Fig. 4—Constellation and error plot for 16-QAM 6-Element AOA = 45°; Network structure 6-12-6-1, $\mu = 0.005$, $\alpha_{\text{hidden}} = 0.1$, $\alpha_{\text{output}} = 0.1$, $\beta = 3.0$
Fig. 5—Constellation and error plot for 64-QAM 8-Element AOA = 75°; Network structure 8-8-1, $\mu = 0.0005$, $\alpha_{\text{hidden}} = 0.7$, $\alpha_{\text{output}} = 0.7$, $\beta = 7.0$

Fig. 6—Desired and adapted array pattern for 4-QAM 4-Element AOA = 75°; Network structure 4-4-1, $\mu = 0.0009$, $\alpha_{\text{hidden}} = 0.7$, $\alpha_{\text{output}} = 0.7$, $\beta = 1.0$

Fig. 7—Desired and adapted array pattern for 16-QAM 6-Element AOA = 45°; Network structure 6-12-6-1, $\mu = 0.005$, $\alpha_{\text{hidden}} = 0.1$, $\alpha_{\text{output}} = 0.1$, $\beta = 3.0$
formed ideally. In fact, it is the only phase at each element which is important for deciding the main lobe of the beam pattern and the modulus part plays a role towards contributing the gain. However, it affects the power distribution in side-lobes and decides the overall pattern. It is found that DDSA-NE is capable of adapting AOA in each case with acceptable limits of variations as shown in Table 1.

6 Conclusion

A decision directed approach for smart antenna has been presented which uses complex multilayer perceptron as a neural estimator for deconvolving the channel effects and extracting the spatial signature of the received signal. The decision direction is achieved using a Bussgang technique for blind adaptation of array weights. Results for different cases of AOA at 4, 6, and 8 element array have been presented. Simulation studies confirm the effectiveness of the approach in estimating the AOA of signal of interest for 4, 16, and 64 QAM formats and obtaining the weights for beamforming.

Apart from two important criteria, i.e. computational complexity and convergence properties for evaluating any adaptive signal processing scheme, which have direct bearing on suitability for being chosen to implement the scheme, several other properties may also be considered. Some of these properties of interest include resolution, sensitivity, variance, bias, error performance, etc. With different signal formats, transmission schemes, channel conditions, and operational requirements like hand-offs, it is hardly

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**Table 2—**Estimated weights for beamforming by DDSA-NE

<table>
<thead>
<tr>
<th>Case 1*</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
<th>Case 5</th>
<th>Case 6*</th>
<th>Case 7</th>
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<td>0.876</td>
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</tr>
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<td>51.276</td>
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<tr>
<td>0.886</td>
<td>67.339</td>
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</tr>
</tbody>
</table>

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Fig. 8—Desired and adapted array pattern for 64-QAM 8-Element AOA = 75°; Network structure 8-8-1, \(\mu = 0.0005\), \(\alpha_{\text{hidden}} = 0.7\), \(\alpha_{\text{output}} = 0.7\), \(\beta = 7.0\)
possible to compare smart antenna schemes on a single account. The results obtained in the proposed decision directed scheme using neural estimation are comparable to results reported (in Ref. 4) on account of identification of principal lobe direction in beamforming.

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References