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COMPARISON OF THE PERFORMANCE OF ARTIFICIAL NEURAL NETWORK WITH VARIABLE STEP-SIZE ADAPTIVE ALGORITHMS FOR THE BEAMFORMING OF SMART ANTENNA FOR CELLULAR NETWORKS

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Abstract. *A smart antenna is an antenna array that uses spatial diversity to identify the desired mobile station (MS) and reject the unwanted interference signal in a cellular network. Generally, adaptive signal processing algorithms are used for smart antenna beamforming, and one of the most common algorithms is the least mean square (LMS) algorithm. Here, the artificial neural network (ANN) is used for beamforming of smart antennas, and the performance of the ANN is compared with the performance of variable step-size LMS (VS-LMS) and variable step-size sign LMS (VS-SLMS) algorithms. The ANN has better performance than the VS-LMS and VS-SLMS algorithms for the determination of user and null directions. Lower side lobe levels (SLLs) are achieved using ANN compared to the VS-LMS and VS-SLMS algorithms. The reduction of SLL from about 3.5 dB to 8.5 dB is achieved using ANN compared to signal processing algorithms.*

Key words: *Smart antenna, artificial neural network, signal processing, variable step-size, beamforming, SLL*

1. Introduction

Smart antenna technology improves overall service quality in cellular communication which provide radiation beams to users while producing nulls for interferers [1]. The function of a smart antenna system in a 3-sector cellular network is shown in Fig. 1. The system uses a signal processing algorithm [1-4] to achieve this adaptive system. The smart antenna is the key technology for 4^{th} generation (4G) wireless access and beyond [5, 6].

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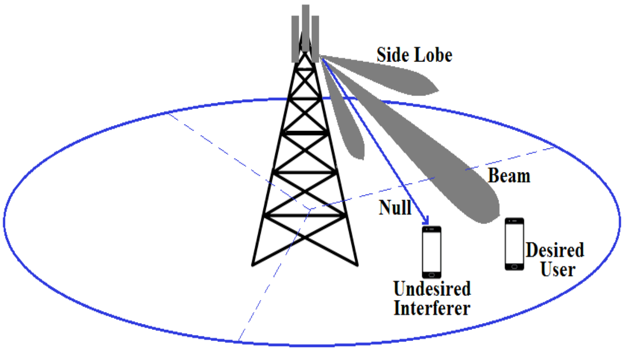

Fig. 1 Smart antenna in an cellular network

The adaptive SAS first identifies the signal's DOA before forming a retro-directive main beam [1]. Multiple Signal Classification (MUSIC) and Estimation of Signal Parameter via Rotational Invariance Technique (ESPRIT) are widely used DOA estimation algorithms [7, 8]. In a cellular network, instead of sending power over the whole cellular zone, a smart antenna produces a beam towards the desired user only. The applications of machine learning (ML) algorithms in smart antenna design is reported in [1].

2. Related Work

There are several beamforming algorithms [9, 10] which include the LMS [1, 11, 12], the recursive least square (RLS) [13], and the sample matrix inverse (SMI) algorithms [14]. The VS-LMS algorithm provides [11] lower SLL. In [14, 15], the VS-LMS algorithm is used for the improved adaptive beamforming of doubly crossed uniform linear arrays. In order to achieve better convergence in adaptive beamforming, variable step-size LMS and its variants are proposed in [16]. Based on past data, in the ML method, a machine learns and improves on its own [17, 18, 19]. The use of ANN for SAS design is suggested in the review paper [20-22]. An overview of the application of ML methods for antenna and antenna array modelling is explained in [23]. A recurrent neural network is proposed to minimize SLL [24]. In [25-27], neural network and deep learning based neural network for adaptive beamforming are reported. According to reported related work, signal processing algorithms appear to be used for the design of SAS in the majority of cases [1]. The design of SAS using machine learning avoids the use of signal processors. The use of machine learning algorithms for SAS design is relatively new, and not many investigations have been reported on it to date. Also, reports on the performance comparison between ANN and signal processing algorithms for the design of smart antennas are not available in the literature.

In this paper, the performance of the ANN method for the design of smart antennas is compared with the signal processing algorithms. The ANN, VS-LMS, and VS-SLMS algorithms are implemented using MATLAB programming. The deviation of beam directions using ANN is negligible from the desired beam directions compared to signal processing methods. The reduction of SLL is necessary for minimizing interference in communication, and using ANN, reduced SLLs are achieved compared to VS-SLMS and VS-LMS algorithms.

3. Artificial Neural Network and Signal Processing Algorithms

Artificial neural network (ANN) is a widely used ML algorithm [27, 28], and ANN is a sub-category of deep learning. In a multi-layer neural network, ANN consists of an input layer, multiple hidden layers, and an output layer. The simple model of a multilayer perceptron network for ANN is shown in Fig. 2 using random weights and the weighted sum of inputs is passed through a non-linear activation function. The signal flows from left to right, which is 'forward pass'. The output is compared with the training data to calculate the error. Then in the 'backward pass', from right to left, it propagates the error to every node using back propagation. Accordingly, to reduce the error, weights are adjusted unless the required output is obtained [1].

Mainly, the signal processing algorithm is used to design a smart antenna [3, 29, 30]. In this paper, the performance of ANN for the beamforming of smart antennas is compared with the performances of the VS-SLMS and VS-LMS algorithms.

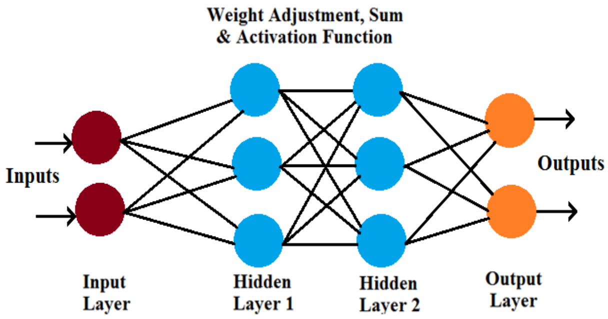

Fig. 2 Artificial neural network architecture

The LMS algorithm incorporates an iterative procedure for successive corrections to the weight vector to obtain minimum mean square error [2, 11, 29]. The error $e(n)$ between the desired signal $d(n)$ and array output $y(n)$ is [15]

$$e(n) = d(n) - y(n) \tag{1}$$

The weight vector update equation in the LMS algorithm is

$$w(n+1) = w(n) + \mu\, x(n)\, e^{*}(n) \tag{2}$$

here, μ is the step-size parameter, complex conjugate of e(n) is e*(n) and $x(n)= [x_1(n), x_2(n)$ ------$x_N(n)]$ is the signal, received by the antennas [31].

The rate of convergence is determined by the step-size parameter μ, which is fixed in the LMS algorithm. In variable step-size algorithms, μ varies, and convergence becomes better. In the VS-LMS algorithm, μ varies during weight updating according to the formula [31]

$$\mu_{n+1} = \alpha\mu_n + \delta\varepsilon_n, \text{ if } 0<\mu_{n+1}< \mu_{max} \tag{3}$$

$$= \mu_{max}, \text{ otherwise}$$

where, maximum value of μ is μ_{max} and 'α' and 'δ' are the constant parameters [11, 32, 33] and in simulation, δ =0.0003 and α =0.95. The weight update equation in VS-LMS algorithm is [1]

$$w(n+1) = w(n) + \mu_{n+1}\, x(n)\, e^{*}(n) \tag{4}$$

In the Sign LMS (SLMS), the sign of the error is used for weight update. Sign (also called signed regressor) LMS is used for a faster adaptation process [34]. In VS-SLMS algorithm, the step size μ varies according to (3). The weight updating in the VS-SLMS algorithm is

$$w(n+1) = w(n) + \mu_{n+1} e^{*}(n) sgn[x(n)] \tag{5}$$

$$\begin{aligned} sgn[x(n)] &= 1; \quad for\ x(n) > 0 \\ &= 0; \quad for\ x(n) = 0 \\ &= -1; \quad for\ x(n) < 0 \end{aligned} \tag{6}$$

4. Smart Antenna Design Using ANN, VS-LMS, and VS-SLMS Algorithms

In this work, smart antennas with a uniform linear array (ULA) of isotropic antennas are considered (Fig. 3). The uniform antenna separation is 'd'.

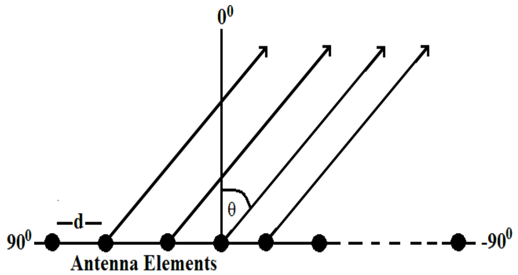

Fig. 3 Uniform linear antenna array

The array factor (*AF*) with a principal beam at an angle θ, is [3]

$$AF(\theta) = \sum_{n=1}^{N} I_0 e^{j(n-1)(\beta d sin\theta + \alpha)} = \sum_{n=1}^{N} I_0 e^{j(n-1)(\frac{2\pi d}{\lambda} sin\theta + \alpha)} \tag{7}$$

where, 'N' is the total number of antenna elements, I_0 is the amplitude of current fed to the antennas, and phase factor $\beta=2\pi/\lambda$ at wavelength λ and the required progressive phase shift in the desired beam direction θ^0 from the broadside direction is [11] $\alpha = -\beta d sin\theta^0$. The cost function for beamforming using *ANN* and signal processing methods is (7). The ratio of array factor (*AF*) to maximum value of array factor (AF_{max}) [11] is the normalized array factor, $AF_{norm} = \left|\frac{AF}{AF_{max}}\right|$

In this work, ULAs of 10, 12, 16, and 20 elements (N=10, N=12, N=16, N=20) with spacing of $d=\lambda/2$ is considered at 1800 MHz [1]. The desired beam (user) direction (BD) is θ_s and the desired null (interferer) direction (ND) is θ_I. For the beamforming using ANN, from the different combinations of f, d, θ_s and θ_I, data set of matrix dimension [2205X25] is created. The *ANN* network consists of 3 input parameters, 2 input variables, 2 hidden layers, and 20 output variables (in the case of N=10) [1]. The first and second hidden layers have 20 neurons and 5 neurons, respectively. The two independent input variables are θ_S, the *BD* , and θ_I, the *ND*. The three input parameters are frequency (f), inter-element spacing (d), and phase constant (β). The 20 output variables are for an antenna array of 10 antenna elements. 10 variables are for the real parts of the weight, and 10 variables are for the imaginary parts of the weight. In ANN simulation, the resilient back propagation algorithm [26] is used as a training algorithm. In ANN, number of run is 1000, learning rate initialization is 0.01 and the tolerance value is 10^{-5}. After training and testing, 10 complex weights are found, and these weights are used for beamforming using the cost function [1].

The VS-SLMS, and VS-LMS algorithms are used for the beam generation of the ULA [11]. Four ULAs with the number of antenna elements N=10, N=12, N=16 and N=20 are considered with different BD and ND. Weight updating equations (4) and (5) with a cost function of (7) are used for beamforming. The number of iterations is 1000 in all cases. The flowchart for the implementation of variable step-size algorithms is shown in Fig. 4.

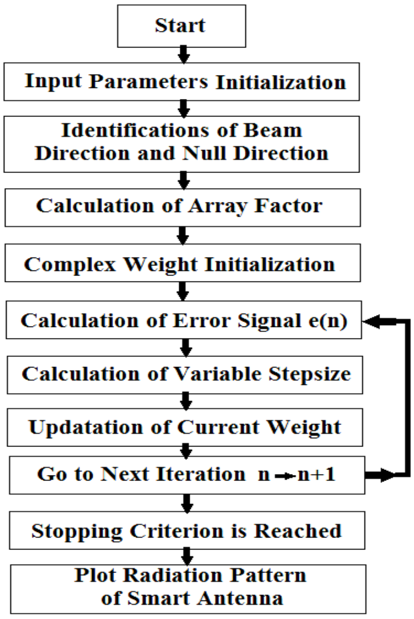

Fig. 4 Flowchart for the implementation of VS-LMS and VS-SLMS algorithms

Adaptive beams of smart antennas of N=10, N=16, and N=20 with inter-element spacing of d=0.5λ obtained using ANN, VS-LMS, and VS-SLMS algorithms are plotted in Figs. 5, 6, and 7 respectively. In Fig. 5, BD=0^0, ND=12^0, in Fig.6 BD=10^0, ND=22^0; and in Fig. 7, BD=20^0, ND=32^0.

To obtain the results of Figs. 5-7, ANN, VS-LMS, and VS-SLMS are simulated for 1000 iterations/epochs. In Fig. 5, for N=10, the maximum SLLs obtained for ANN, VS-SLMS, and VS-LMS are -13.3 dB, -9.98 dB, and -4.7 dB, respectively. In Fig. 6, for N=16, the maximum SLLs obtained for ANN, VS-SLMS, and VS-LMS are -13.05 dB, -8.72 dB, and -9.4 dB respectively. In Fig. 7, for N=20, the maximum SLLs obtained for ANN, VS-

SLMS, and VS-LMS are -13.4 dB, -9.88 dB, and -9.0 dB, respectively. In all the cases deviations of BD and ND from desired values are minimum ANN. Therefore, the performance of ANN for beamforming of smart antennas is better than that of VS-SLMS, and VS-LMS algorithms.

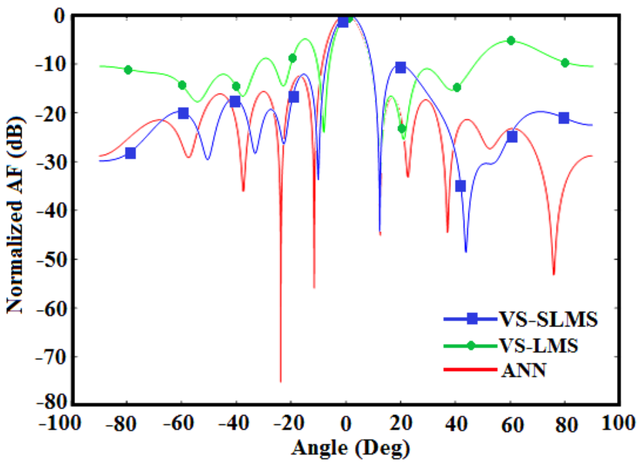

Fig. 5 Radiation beam using ANN, VS-LMS, and VS-SLMS for N=10

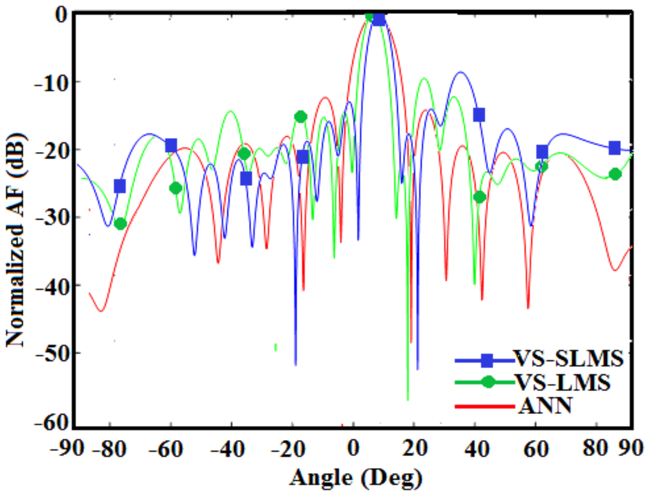

Fig. 6 Radiation beam using ANN, VS-LMS, and VS-SLMS for N=16

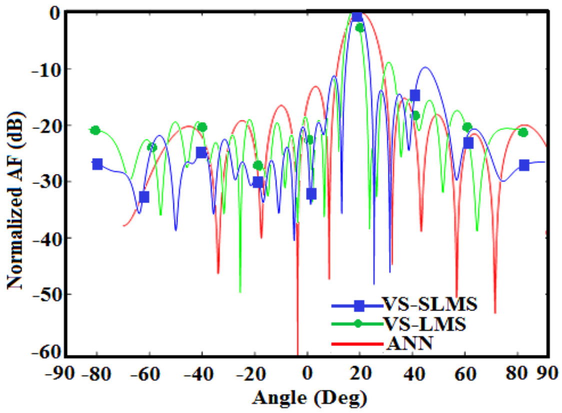

Fig. 7 Radiation beam using ANN, VS-LMS, and VS-SLMS for N=20

The results, obtained using ANN, are compared with the signal processing algorithms in Table 1.

Table 1 Comparison of results between ANN and signal processing algorithms

No. of elements	Algorithm	Desired BD	Obtained BD	Desired ND	Obtained ND	SLL_{max}
N=10	ANN	0°	0.0°	12°	11.9°	-13.3 dB
	VS-SLMS	0°	0.7°	12°	12.3°	-9.98 dB
	VS-LMS	0°	0.9°	12°	11.7°	-4.70 dB
N=12	ANN	15°	15.1°	30°	30.1°	-13.02 dB
	VS-SLMS	15°	14.5°	30°	29.5°	-8.69 dB
	VS-LMS	15°	15.4°	30°	27.6°	-9.15 dB
N=16	ANN	10°	10.1°	22°	22.1°	-13.05 dB
	VS-SLMS	10°	10.4°	22°	22.3°	-8.72 dB
	VS-LMS	10°	9.6°	22°	21.6°	-9.40 dB
N=20	ANN	20°	20.0°	32°	32.0°	-13.40 dB
	VS-SLMS	20°	19.0°	32°	31.8°	-9.88 dB
	VS-LMS	20°	19.6°	32°	26.5°	-9.00 dB

In Table 1, the deviations of BD and ND from the desired values are less for ANN than for VS-LMS and VS-SLMS. Lower SLLs are obtained for ANN in all the cases. The variations in maximum SLLs with the number of antennas in the array are compared in Fig. 8. Using ANN, an SLL reduction of about 8.5 dB is achieved for N=10 compared to VS-LMS. For N=12, N=16, and N=20, a SLL reduction of about 3.5 dB is obtained in ANN compared to signal processing algorithms.

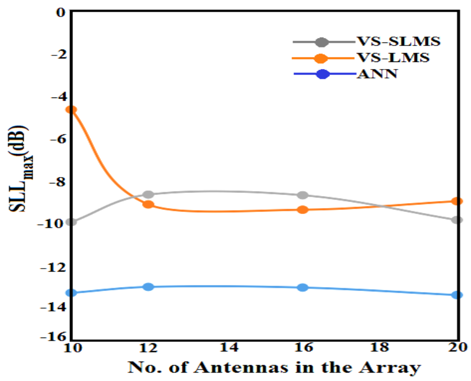

Fig. 8 Variation of maximum SLL with number of antenna elements in the array

The mean square error (MSE) graphs for VS-LMS, VS-SLMS, and ANN are shown in Fig. 9 for N=10, BD=0° and ND=12°.

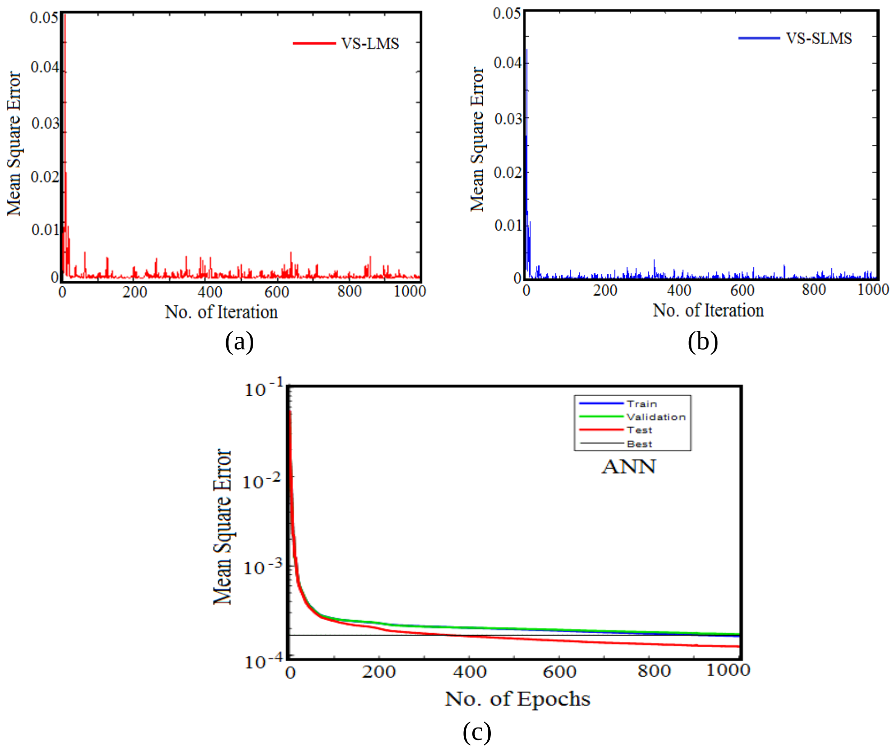

Fig. 9 MSE curves for (a) VS-LMS (b) VS-SLMS (c) ANN

The convergence of the ANN algorithm is faster than that of the variable step-size adaptive algorithms.

The results for the beamforming of the smart antennas, using ANN are compared with the published results [16, 17, 25, 27, 35] in Table 2.

Table 2 Performance comparison of ANN with other published results

References	Beamforming method	Parameters	Maximum SLL
Ref [16]	VS-SLMS	ULA with N=4, d=λ/2, BD=20^0	-11.5 dB
Ref [17]	VS-NLMS	ULA with N=10, d=λ/2, BD=0^0	-12.1 dB
Ref [25]	Recurrent neural network (RNN)	ULA with N=32, d=λ/2, BD=0^0	-7.5 dB
Ref [25]	RNN	ULA with N=16, d=λ/2, BD=-10^0	-8.5 dB
Ref [27]	RNN based on the gated recurrent unit	ULA with N=16, d=λ/2, BD=100^0	-11.5 dB
Ref [35]	Elman RNN	ULA with N=5, d=λ/2, BD=30^0	-11.5 dB
This paper	ANN	ULA with N=10, d=λ/2, BD=0^0	-13.3 dB
This paper	ANN	ULA with N=16, d=λ/2, BD=10^0	-13.05 dB
This paper	ANN	ULA with N=20, d=λ/2, BD=20^0	-13.4 dB

One of the main sources of interference in a cellular network is the side lobes of the desired radiation beam. In Table 2, lower SLLs are achieved using ANN, presented in this paper.

5. Conclusion

The performance of the ANN method for the design of smart antennas is compared with the signal processing algorithms. The ANN shows better performance for achieving the desired BD and ND than other methods. For low interference low SLL is desired in a cellular network, and using ANN, lower SLLs are achieved compared to VS-LMS and VS-SLMS algorithms. The ML method of beamforming avoids the use of a signal processor in the SAS. The theory and simulation are easier for the ANN method than other ML algorithms. But the simulation time in the ANN algorithm is longer than in the signal processing methods. The average time in ANN simulation is 66 seconds, whereas for VS-LMS or VS-VSSLMS, it is 25 seconds.

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