International Journal of Scientific & Engineering Research Volume 8, Issue 12, December-2017
ISSN 2229-5518

Enhanced RLS in Smart Antennas for Long Range Communication Networks

Peter Nnabugwu Chuku
Department of Electrical Eng., FSATI,
Tshwane University of Technology
Pretoria, South Africa
chukunp@gmail.com

Thomas Otieno Olwal
Department of Electrical Eng., FSATI,
Tshwane University of Technology
Pretoria, South Africa
olwalTO@tut.ac.za

Karim Djouani
Department of Electrical Eng., FSAT,
Tshwane University of Technology
Pretoria, South Africa
djouaniK@tut.ac.za

Abstract—The utilisation of smart antenna (SA) techniques in future wireless and cellular networks is expected to have an impact on the efficient use of the spectrum and the optimization of service quality. This is because SAs can enhance the maximization of output power of the signal in desired directions amongst a whole lot of functions. In spite of these benefits of SAs, long range communications still face unsolved challenges such as signal fading. Therefore, this paper focuses on enhancing the recursive least squares (RLS) in SA design for long range communication networks. The conventional RLS algorithm does not need any matrix inversion computations because the inverse correlation matrix is determined directly. Therefore, the RLS saves computational power. Hence, we have enhanced the RLS algorithm by introducing a constant $\boldsymbol{m}$ to the gain factor in order to yield an improved gain vector. Results obtained from our simulations show that the enhanced RLS reduces mean square error (MSE), smoothens filter output and improves SNR when compared to the conventional methods. These benefits further result in antenna the gain improvement leading to an increased range and directivity of the smart antenna over a long range communication networks.

Index Terms— Smart antennas; direction of arrival; adaptive arrays; switched beam arrays; digital signal processing; mobile communication; wireless networks.

1 Introduction

Over the past decade, wireless and mobile communications have experienced a rapid growth in the demand for the provision of new wireless multimedia services such as: internet access, multimedia data transfer and video conferencing [1]. In order to meet such demands and to overcome the limited capacity of the single input single output (SISO) systems, the use of multiple element antennas (MEAs) has recently emerged as a solution [2]. Smart antenna (SA) is defined as a system which combines an antenna array with a digital signal processing capability in order to transmit and receive in an adaptive, spatially and sensitive manner [18]. SAs have the property of spatial filtering and this property makes it possible for the SA to receive energy from a particular direction whilst at the same time, blocking the energy from getting to another direction. SAs can also be referred to as adaptive array antennas or simply multiple input, multiple output (MIMO) antennas having antenna arrays with smart signal processing algorithms used to identify spatial signal signature such as the direction of arrival (DOA) of the signal [3]. The SA can be used to calculate beamforming vectors which track and locate the antenna beam on the mobile receivers in a cellular network.

There are two main functions of SAs which are performing direction of arrival (DOA) and beamforming respectively [3]. SA designs involve the processing of signals induced on an array of antennas. Beamforming is an ability achieved by SAs to increase the range and capacity of a signal that is transmitted or received.

Adaptive filtering is a technique in which the weights of an adaptive antenna are updated [19]. In recent years, adaptive algorithms have been used to perform the function of filtering. The performance of most adaptive algorithms largely depends on the condition of their signal and filter order. Whereas, the performance of the recursive least squares (RLS) algorithm is dependent on the forgetting factor λ. A complex weight is the combination of the relative amplitude and phase shift for each antenna [4]. The RLS algorithm is known for its superiority over most adaptive algorithms like the least mean squares (LMS), constant modulus algorithm (CMA), etc. because of its faster rate of convergence and smaller mean square error (MSE) [5]. Several techniques have been proposed by authors in [4, 5 and 9] that provided significant improvements in the performance of the conventional RLS algorithm. However, these improvements came with a high cost in computational complexity [6].

This paper presents an enhanced RLS based design that improves the gain and directivity of SA over long range communication networks. We build our approach from the argument that the gain vector $k(n)$ is essential in the performance of the RLS algorithm. This is because the output of the RLS filter is usually computed when there is a convolution of the input sample, tap coefficients $u(n)$ and the weight vector $w(n)$. The weight vector on the other hand is updated by taking the product of the gain vector $k(n)$ with the error signal $e(n)$ [20]. Hence, it is for this reason that we have proposed the enhancement of the gain vector $k(n)$ in this paper. We infer that an enhancement of the gain vector $k(n)$ will lead to a consequential improvement in the convergence rate of the RLS algorithm.

The rest of the paper is organised as follows: section II presents literature review on related work, section III focuses on our system model, section IV shows the performance evaluation and results of the enhanced RLS algorithm and section V concludes the paper. In sections VI and VII, we indicate the acknowledgements and references respectively.

2 Related Work

We see from literature in [7] that adaptive antenna arrays incorporate more intelligence into their control system than the switched-beam arrays. The adaptive array model utilizes digital algorithms which produces beamforming in a noisy wireless network. The figure below (fig. 1) illustrates a beamforming signal of an adaptive array antenna to a specific user which also has some interfering signals that are of the same frequency as the beamforming signal from different directions. These interfering signals are rejected by varying the weights varying the weights of each antenna element in the array.

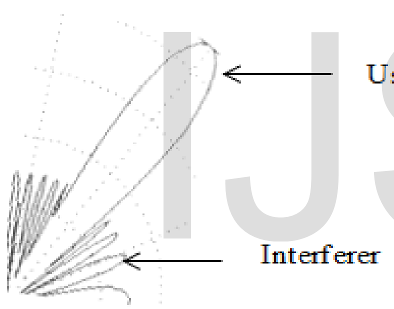


Figure 1: Adaptive array antenna [8]

Authors in [9] presented an overview of the benefits of smart antenna transceiver architecture. They also presented the important shift in the appropriation of SAs in future systems such as: re-configurability to varying channel propagation and network conditions, cross-layer optimization, multi-user diversity. However, there were challenges such as the design of a suitable simulation methodology and the accurate modelling of channel characteristics, interference, implementation losses that were presented in [9]. Hybrid schemes that combine space-time coding and beamforming were proposed in [10]. These schemes introduce precoding to exploit the available CSI when optimizing a certain criterion (e.g., pair-wise error probability).

A methodical comparison of the performance of different adaptive algorithms for beamforming for SA system was presented in [11]. The study also considered the strengths and weaknesses of the three algorithms that were used. They were namely: Recursive Least Squares (RLS), Least Mean Squares (LMS) and Constant Modulus Algorithm (CMA). It was also stated in [11] that the high error rate experienced in a single antenna element is due to the fact that the antenna would have to provide coverage to enhanced number of users which are more than its capacity, so the rate of errors increases. The study showed that interference rejection is best accomplished in the CMA because it has the ability to cancel out interfering signals coming from neighbouring networks. Studies further showed that the LMS algorithm incorporates an iterative technique that successively updates the weight vector in a direction which is opposite to the gradient vector. This technique eventually makes the LMS minimize the mean square error (MSE) when compared to other algorithms. The convergence rate of RLS is faster than LMS because the RLS algorithm does not require any matrix inversion computation as the inverse correlation matrix is directly computed [12]. Studies in [13] further showed that the RLS algorithm only requires a reference signal and information for the correlation matrix in order to compute. These qualities made the RLS algorithm the best algorithm for implementation on the base station (BS) of a SA system. The limiting factor in this study is the closeness in angles that the interference and user signals have between each other because the SNR had been reduced from 10 dB to 2 dB.

Authors in [13] used various algorithms to adapt the weights of the SA arrays so as to augment the output power of the signal in the expected direction and curtail the power in the unwanted direction. Also considered were different types of arrays such as: linear, circular and planar arrays. Different algorithms were used to adjust the weights in SA systems. The limitation faced in [13] is that both LMS and RLS need a reference signal which has to be provided by CMA. These arrays are used to adapt the weights of the array which gives the expected parameters (main beam steering, deep null placement in the undesired signal direction, etc.) under a noisy communication channel. Conclusions were made in [13] that the problem of slow convergence experienced in the LMS algorithm is solved by the RLS algorithm.

Based on the concluding remarks on [11], [13] and [14], the RLS algorithm was suggested as the best algorithm that will achieve the best beamforming towards desired signals. However, some limitations were highlighted in the RLS algorithm based on its unsatisfactory response to nullify co channel interference (CCI) [15]. Therefore in this study, we seek to enhance SA schemes for beamforming over long range of communications by further developing the RLS algorithm in such a way that a constant m is introduced to the gain factor in order to yield an improved gain vector.

3 System Model

In this section, we model enhanced RLS algorithm by adapting the weights $w(n)$ of the filter recursively. And in order to adapt the weights, the error signal $e(n)$ and the gain factor $k(n)$ must be determined. The error signal are determined by calculating the difference between the desired signal $d(n)$ and the output signal $y(n)$ of the filter. Hence, our work in this chapter is to determine an improved value of the gain factor $k(n)$which will yield better the weights of the RLS filter. Figure 2 illustrates how the weights $w(n)$ of the RLS filter can be computed.

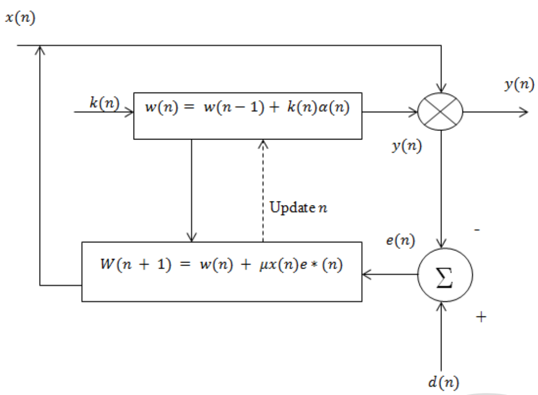


Figure 2: Adaptive weight computation

The correlation matrix can be used to derive the RLS algorithm which has some inefficient calculations as it does not consist of some necessary variables that comprise the RLS algorithm. However, authors in [16] suggested that in order to avoid the computational inefficient calculations of $\Phi^{-1}(n)$, it is advisable to deploy matrix inversion. Matrix inversion is usually deployed to avoid computationally inefficient calculations of $\Phi^{-1}(n)$.

Following such matrix inversion, the autocorrelation of the tap input vector $u(n)$ of order M-by-M is given by

$$\Phi^{-1}(n) = \sum_{i=1}^{n} \lambda^{n-1} u(i) u^{H}(i) + \delta \lambda^{n} I \quad (1)$$

$\delta$is the Regularizing parameter and λ is the forgetting factor. M-by-1 cross-correlation matrix of the tap input vector $u(n)$ and $d(n)$ is the desired response which is given by:

$$z(n) = \sum_{i=1}^{n} \lambda^{-1} u(i) d(i) \quad (2)$$

For RLS method, tap weight vector $w(n)$ can be calculated as

$$\Phi(n) w(n) = z(n) \text{ OR}$$

$$w(n) = \Phi^{-1}(n) z(n) \quad (3)$$

The final equation after using the matrix inversion method cited by [16] is:

$$\Phi^{-1}(n) = \lambda^{-1}\Phi^{-1}(n-1) - \frac{\lambda^{-2}\Phi^{-1}(n-1)u(n)u^{H}(n)\Phi^{-1}(n-1)}{1 + \lambda^{-1}u^{H}(n)\Phi^{-1}(n-1)u(n)} \quad (4)$$

$k(n)$is the M-by-1 vector and is known as the gain vector and it is defined by the tap input vector $u(n)$ which is transformed by the inverse of the correlation matrix $\Phi^{-1}(n)$

$$k(n) = \Phi^{-1}(n) u(n) \quad (5)$$

In order to obtain the RLS weight vector from (5),

$$w(n) = \Phi^{-1}(n)z(n-1) + \Phi^{-1}(n)d(n) - k(n)u^{H}(n)\Phi^{-1}(n-1)z(n-1) \quad (6)$$

After simplifying the weight vector $w(n)$ in (6), the simplified equation for the weight vector is now:

$$w(n) = w(n-1) + k(n)\, e(n), \quad (7)$$

where the error signal$e(n)$ is calculated as

$$e(n) = d(n) - y(n). \quad (8)$$

$P(n)$ is the inverse correlation matrix at step n;

$$P(n) = \Phi - 1(n). \quad (9)$$

Here, our enhanced gain factor $k(n)$ is given as

$$k(n) = \frac{\pi(n)}{m \times \lambda + u^{H}(n)\pi(n)} , \quad (10)$$

where$\pi(n)$ is denoted as

$$\pi(n) = P(n-1)u(n) \quad (11)$$

We initialize our algorithm by setting

Step (i) The weight vector, w(0) = 0

$$P(0) = \delta^{-1}\mathbf{I}$$

Step (ii) And the value for δ depends on the SNR i.e,

$$\delta = \begin{cases} small\ positive\ constant\ for\ high\ SNR \\ large\ positive\ constant\ for\ low\ SNR \end{cases}.$$

Step (iii) The value of δ can be verified based on regularization grounds.

Step (iv) And for each instant of time, n = 1,2,3,,4,…

Step (v)Compute:

$$\pi(n) = P(n-1)u(n),$$

$$k(n) = \frac{\pi(n)}{m \times \lambda + u^H(n)\pi(n)} \quad \text{and}$$

$$P(n) = \frac{P(n-1) - k(n) * \pi(n)}{\lambda}$$

The uniqueness of our improved algorithm relates to introducing a constant m to the gain factor $k(n)$ of the RLS algorithm in order to improve the gain and directivity of the smart antenna used in long range communication networks. The result of this enhancement on the gain factor will influence the general performance of the weights at the output of the adaptive filter shown below.

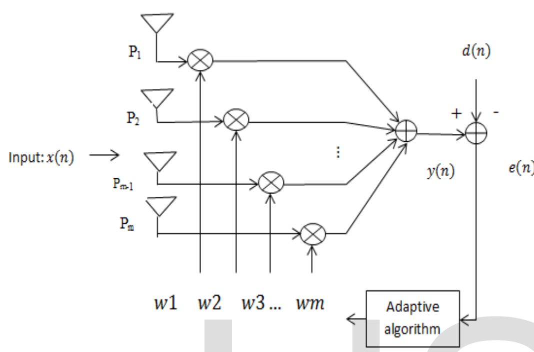


Figure 3: Adaptive Filtering

The RLS algorithm is a deterministic algorithm in the sense that its performance index is the sum of weighted error squares for every given data. The weight vector is updated after every iteration.

The constant m that has been introduced to the gain factor $k(n)$ will be given a value. We have conducted several mathematical computations and further simulations in order to determine the best possible value of m that can be introduced to $k(n)$ so that the weighted output of our RLS filter outperforms the weights of the other adaptive algorithms that have been implemented by smart antenna design. Authors in [17] concluded that the rate of convergence of adaptive algorithms depends upon the value of the step size parameter µ. The value of µ lies between 0 and 1. The optimised value of m was initially obtained through mathematical computations and then, simulation results further affirmed our mathematical computation. The constant m was given numbers between the range of 0.1 and 1.9. The mathematical computation was conducted using the gain constant $k(n)$ in equation 10 above. The results of the mathematical computation showed that $k(n)$ is at an optimum value when m is 0.25. Therefore, we have given the constant m the value of 0.25.

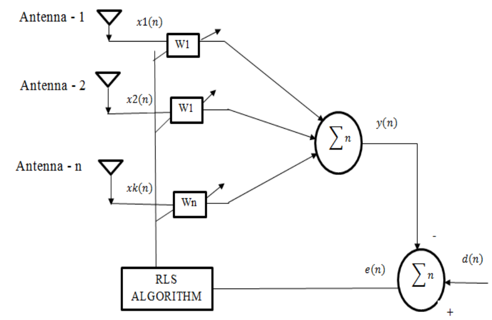


Figure 4: Computation of our RLS algorithm

4 Performance Evaluation And Results

The performance of RLS based model for smart antenna design has been studied by means of MATLAB simulations. In these simulations, we have considered three cases taking into consideration the error curve, system output and the comparison between the filter weights and the estimated weights for three adaptive algorithms namely: LMS, the conventional RLS and our enhanced RLS algorithm. The following parameters have been considered for simulation purpose:

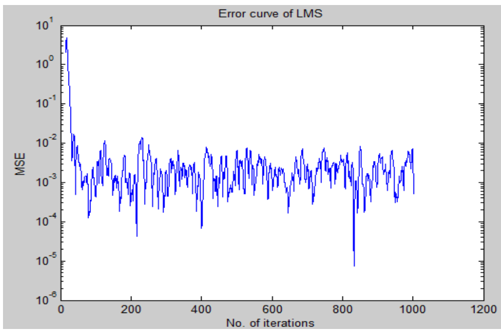
TABLE I

SIMULATION PARAMETERS

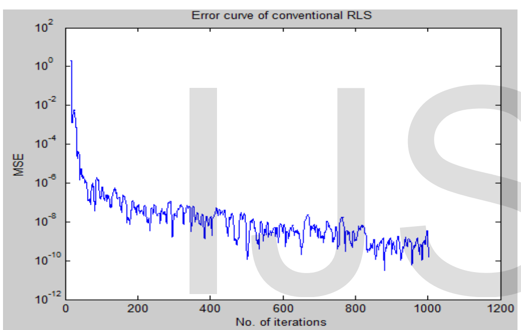
S/N	Parameters	Specification	Reason
1	Number of antenna elements	5	5 elements are used so that our simulations will be based on an antenna with few elements
2	Number of system points	2000	It is always advisable to base your test within a wide range of samples.
3	Forgetting factor	0.99	A forgetting factor of 0.99 is a perfect value for the RLS algorithm.
4	Number of training points	50	Gives a large number of iterative tests.

The results of the three experiments are presented in figs. 4, 5 and 6 below:

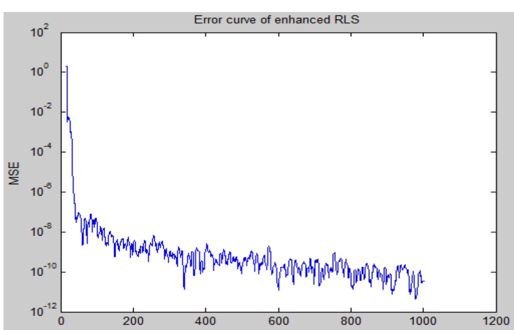
The reason for the simulations is to see if the enhancment we have made on the gain factor $k(n)$ has an effect on the performance of the RLS algorithms. Firstly, we run simulations on the mean square errors (MSE). Based on the MSE curves in fig. 4 (a, b and c), it can be observed that the error curve of the enhanced RLS algorithm assumes an error value of below 10^{-8} before the 200^{th} iteration. When compared to the error values of the conventional RLS algorithm, we see that the error cure only assumes a value less than 10^{-8} after the 500^{th} iteration. We also notice a clearer distinction between our enhanced RLS algorithm and the LMS algorithm in terms of the error values of the MSE. The value of the MSE for the LMS algorithm borders between 10^{-2} and 10^{-3}. The value of the error curve as can be observed in fig. 4a does not come as low as that of our enhanced RLS algorithm. These results signify lesser errors occurring in our enhanced RLS algorithm. Through these results, we can suggest that the enhanced RLS algorithm provides better directivity and a better SNR over the LMS algorithm and the conventional RLS algorithm using the values of the mean square error as discussed above.



(a) LMS error



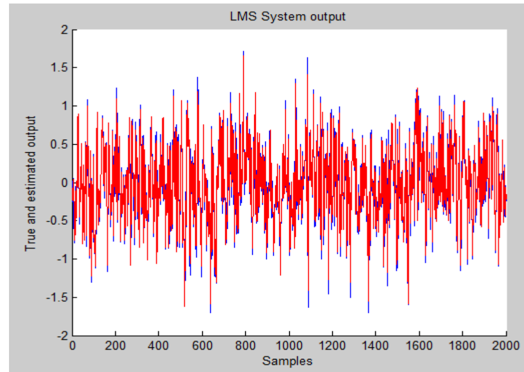
(b) Conventional RLS error



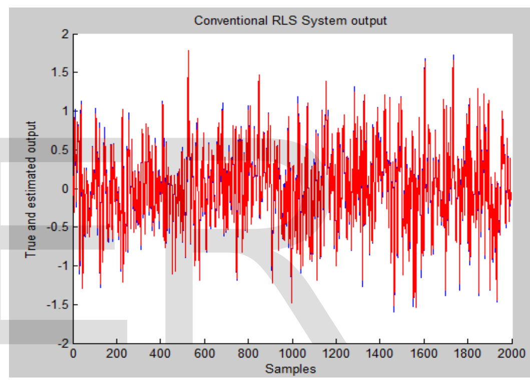
(c) Enhanced RLS error

Figure 4 : Error curve comparison

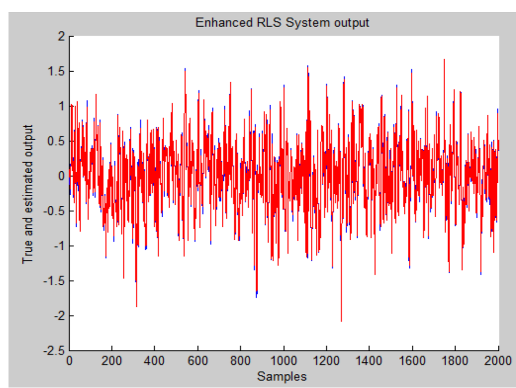
Secondly, the graphs in fig. 5a, 5b and 5c respectively (below) show the system outputs of the LMS, conventional RLS and the enhanced RLS algorithms that are being compared. Based on these results, the following can be observed: in fig. 5a, the waveform of the LMS algorithm initially displayed a lot of noise and spikes. In fig. 5b, the pattern of the waveform became clear with fewer spikes signifying a less noisy output. Whereas, the enhanced RLS algorithm (fig. 5c) displayed almost a smooth waveform at the filter's output; thus signifying a lesser noisy channel.



(a) LMS system output



(b) Conventional RLS system output

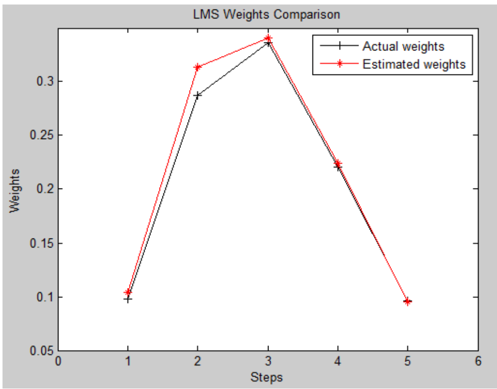


(c) Enhanced RLS system output

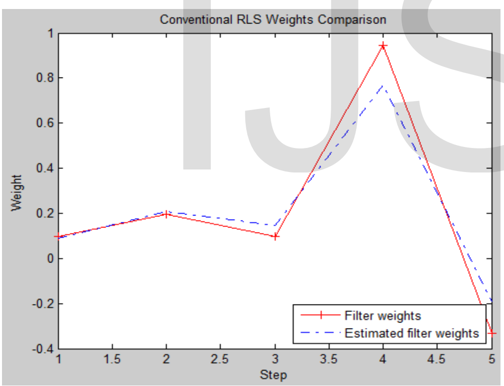
Figure 5 : Adaptive system output comparisons

The last set of simulations takes into account the weighted output of the adaptive filters that we are comparing in this paper. The weights (vertical - axis) are generated recursively with respect to the number of samples (horizontal - axis).

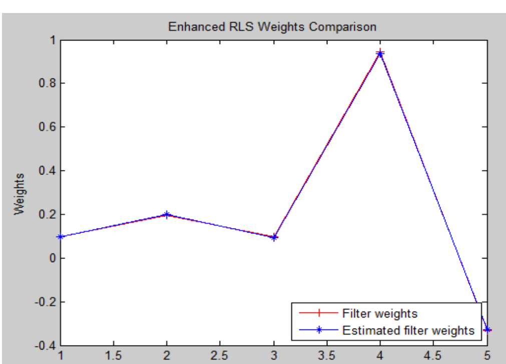
Figure 6 (a, b and c) below illustrates the comparison between the filter weights and estimated weights of the LMS, conventional RLS algorithm and our enhanced RLS algorithm respectively. It can be observed in 6c that as the number of steps increases (on the x-axis), the estimated weights still continue to track the filter weights (enhanced RLS algorithm).



(a) LMS weights comparison



(b) Conventional RLS weights comparison



(c) Enhanced RLS weights comparison

Figure 6 : Comparison of adaptive weights

Hence, both waveforms in 6c track each other. Whereas, it can be observed that the estimated weights in 6b gradually begin to loose track of the filter weights as the number of samples increases. Also, a considerable variation can observed with the LMS algorithm (fig. 6a); after the first sample, the estimated weights begin to drift away from the actual weights.

From all the results of our simulations, it can be observed that our enhanced RLS algorithm out performs both the LMS algorithm and the conventional RLS algorithm.

5 Conclusion

In this paper, an RLS based model for smart antenna design is discussed. We have enhanced the gain factor $k(n)$ of the RLS algorithm in order to improve its performance which results to an increase in the gain and the directivity of the smart antenna. A constant m has been introduced to the gain factor $k(n)$ of the RLS algorithm with an expectation of enhancing the performance of the output of the adaptive antenna. Results of the simulations carried out in figures above, respectively show the following: the comparison of MSE, the comparison of the system outputs of the different adaptive algorithms and the filter weights comparison of the three adaptive algorithms that we selected for comparison. These simulations show that the enhanced RLS algorithm possesses better performance in terms of lower MSE which leads to a quicker rate of convergence and directivity of the adaptive algorithm. Also, the output of the enhanced RLS algorithm shows a smoother waveform thus indicating that it is the best adaptive filter; thus eliminating unwanted noise from surrounding communication networks. Also, when compared to the conventional RLS algorithm and the LMS algorithm, the enhanced RLS algorithm possesses weights that are almost accurate to the estimated weights. Thus, the weight complexity problems usually experienced with adaptive filters have been reduced by the introduction of our adaptive algorithm. Hence, it can be deduced that design proposed in this paper reduces SNR, updates weights speedily and increases the rate of convergence of the RLS algorithm for SAs over long range communication networks.

Acknowledgment

The authors would like to acknowledge Tshwane University of Technology and the National Research Foundation for providing research funding, facilities and equipment for this study.

REFERENCES

[1] R. Kawitkar and D.G. Wakde: "Advances in Smart Antenna System"; Journal of Scientific and Industrial Research, Vol. 64, September 2005, pp. 660-665.

[2] I. Chih-Lin, C. Rowell, S. Han, Z. Xu, G. Li and Z. Pan; 5G Wireless Communication Systems: Prospects and Challenges. IEEE Communications Magazine. February, 2014.

[3] G. V. Tsoulos; Smart antennas for mobile communication systems: benefits and challenges. Electronics & Communication Engineering Journal, April 1999.

[4] L. C. Godara: "Application of Antenna Arrays to Mobile Communications, Part II: Beamforming and Direction-of-Arrival Considerations". Proceedings of IEEE, vol. 85, no. 8, pp. 1195-1245. 1997.

[5] Simon Haykin; "Signal processing: Where Physics and Mathematics meet". IEEE Signal Processing Magazine, 18(4): 6-7; 2001.

[6] B. Ramineni, G. C. Sagar, K. A. Jain, M. S. Ganga Prasad, T. V. Ramakrishna and K. Sarat Kumar: "Comparison and Performance Evaluation of Different Adaptive Beamforming Algorithms in Wireless Communications With Smart Antenna". International Journal of Engineering Research and Applications (IJERA). May-June 2012, pp. 630-633.

[7] P. I. I. Constantine and A. Balanis: "Book on Introduction to Smart Antennas". Department of Electrical Engineering; Arizona State University, Morgan and Claypool, 2007.

[8] R. Joshi and A. Dhande: "Adaptive Beamforming Using LMS Algorithm". International Journal of Research in Engineering and Technology; vol. 3, Issue 05. May 2014.

[9] X. Wang, X. Shi, P. Li, Y. Bai, B. Liu, R. Li and H. Lin; "Smart Antenna Design for GPS/Glonass Anti-Jamming Using Adaptive Beamforming". In Microwave and Millimeter Wave Technology (ICMMT), 2010 International Conference; pages 1149-1152, May 2010.

[10] R. Divya and T. Jayasimha; "Adaptive Beamforming Algorithm for Smart WiMAX Antenna". International Journal of Advance Research in Computer Science and Management Studies; Vol. 2, Issue 5, May 2014.

[11] S.F. Shaukat, M. ul Hassan, R. Farooq, H.U. Saeed and Z. Saleem. Sequential Studies of Beamforming Algorithm for Smart Antenna Systems. World Appl. Sci. J., 6(6): 754-758, 2009.

[12] M. Chryssomallis: "Smart Antennas". IEEE Antennas and Propagation Magazine. Vol. 42, no. 3; pp. 129-138, June 2000.

[13] S. Bellofiore, C. A. Balanis, J. Foutz, and A. S., Spanias: "Smart antenna systems for mobile communication networks". Part 1: overview and antenna design, *IEEE Antennas Propagat. Mag.* 44 (2002), 145-154.

[14] R. L. Ali, A. Ali, Anis-ur-Rehman, S. A. Khan and S. A. Malik; "Adaptive Beamforming Algorithms for Anti-Jamming". International Journal of Signal Processing, Image Processing and Pattern Recognition, Vol. 4, No. 1, March 2011.

[15] F. Albu, J. Kadlec, C. Softley, R. Matousek, A. Hermanek, N. Coleman and A. Fagan: "Implementation of (Normalised) RLS Lattice on Virtex". University of Newcastle upon Tyne, UK.

[16] A. Ali, A. Rehman and R. Ali: "An Improved Gain Vector to Enhance Convergence Characteristics of Recursive Least Squares Algorithm". International Journal of Hybrid Information Technology. Vol. 4, No. 2, April, 2011.

[17] A. Khan: "Beamforming Using Adaptive Algorithms". Telecom department Hazara University Mansehra. Session 2010- 2014.

[18] L. Surenda, S. Shameem and H. Khan: "Performance Comparison of LMS, SMI and RLS Adaptive Beamforming Algorithms for Smart Antennas". IJCST Vol. 3. Issue 2, April – June 2012.

[19] B. D. VanVeenand K. M.Buckley: "Beamforming, a Versatile Approach to Spatial Filtering". IEEE ASSP Magazine. April, 1988.

[20] H. V.Ajmera and M. Z. Ahmed: "Implementation of RLS Algorithm". Advances in Communications, Computing, Networking and Security 7. Fixed and Mobile Communications, University of Plymouth, Plymouth, UK.

Peter N. Chuku obtained his B-tech degree in Electrical Engineering from Tshwane University of Technology (TUT) in 2014. He has worked as a Network Engineer for XDSL Networking Solutions, South Africa. He is currently registered as a Masters student in Electrical Engineering with Tshwane University of Technology, Pretoria South Africa. His research interest is adaptive beamforming techniques in SA designs for long range communications.

Thomas O. Olwal is a professor in Electrical Engineering/ FSATI from Tshwane University of Technology (TUT). His niche area is Telecommunications and Signal Processing.

Karim Djouani is a full professor in Electrical Engineering/ FSATI from Tshwane University of Technology (TUT). His niche area is Control and Image Processing.