Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2021) 29: 663 – 672
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doi:10.3906/elk-2002-82

Low communication parallel distributed adaptive signal processing (LC-PDASP) architecture for processing-inefficient platforms

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Received: 13.02.2020 • **Accepted/Published Online:** 11.09.2020 • **Final Version:** 30.03.2021

Abstract: In this paper, a low communication parallel distributed adaptive signal processing (LC-PDASP) architecture for a group of computationally incapable and inexpensive small platforms is introduced. The proposed architecture is capable of running computationally high adaptive filtering algorithms parallely with minimally low communication overhead. A recursive least square (RLS) adaptive algorithm based on the application of multiple-input multiple-output (MIMO) channel estimation is implemented on the proposed LC-PDASP architecture. Complexity and Communication burden of proposed LC-PDASP architecture are compared with that of conventional PDASP architecture. The comparative analysis shows that the proposed LC-PDASP architecture exhibits low computational complexity and provides an improvement more than of 85% reduced communication burden than the conventional PDASP architecture. Moreover, the proposed LC-PDASP architecture provides fast convergence performance in terms of mean square error (MSE) than the PDASP architecture.

Key words: MIMO channel estimation, distributed adaptive filtering, processing efficient parallel architecture

1. Introduction

In order to reduce the extensive amount of processing over the centralized processor, a distributed adaptive signal processing techniques provide an interactive solution for high definition adaptive filtering algorithms though retaining the accuracy [1, 2]. The adaptive filters based on the distributed techniques are used in many applications, such as military surveillance, factory and transportation instrumentation, environmental parameters estimation and agriculture development [1–3].

One of the particular objectives is that the distributive adaptive solution has potentials to share the bandwidth, computational complexity and power usage are thereby reduced as compared to the centralized solution [1–4]. In [5–7], the consensus based distributed solution is presented. The consensus technique requires two time scales while working on the estimation problem. During the initial time period, each node in the distributed network produces the individual estimate; however, in consensus stage, all the nodes then combine the local estimations and reaching towards the desire estimate. The consensus technique relies on network topology and particular conditions which make its ruled out real time implementation. Furthermore, the incremental distributed technique is introduced in [8–11]. In incremental strategy, all the network nodes use the cyclic pattern to find the estimate of the unknown coefficients with minimum power requirements. Furthermore, in the incremental network, each individual node performs local computations and then share the updated

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information towards the adjacent node. The number of nodes in the incremental network is dependent upon the total iterations which are used to make possible for the convergence of the adaptive algorithm. As compared to centralized solution, the incremental approach reduces the power requirements and improves the autonomy of the network. However, in case of multiple-input multiple-output (MIMO) channel estimation scenario, the consensus and incremental based network techniques facing high communication burden in sense of transferring of complex MIMO channel matrices among the nodes of the network. Likewise, in [12, 13], low communication recursive least square technique is introduced. In this technique, the communication burden reduced by initializing the covariance matrix at each node in the distributed network; however, all the distributed nodes still entail the complex computational complexity of the adaptive algorithm and each node in the network is being idle for $K-1$ iterations, where K is the total number of iterations required for the complete convergence of the adaptive filtering algorithm. Furthermore, in [14], a novel processing-efficient parallel distributed adaptive signal processing (PDASP) architecture is introduced. The PDASP architecture entails lesser computational cost as compared to sequentially operated algorithms [15, 16]; however, the communication burden among the participating nodes is very high which makes a very critical impact on overall execution time of adaptive filtering algorithm.

In this paper, a low communication parallel distributed adaptive signal processing (LC-PDASP) architecture is introduced. In the proposed architecture, each node uses the collaborative strategy though requires limited interaction with the other nodes. The proposed architecture utilizes only two nodes for the complete communication setup which provides the best utilization of low cost devices than the proposed LC RLS scheme [12, 13]. Furthermore, the proposed LC-PDASP scheme exhibits reduced multiplication complexity and communication burden than the conventional PDASP architecture [14]. Moreover, the proposed architecture provides an improvement in mean square error (MSE) than the PDASP architecture. The convergence performance of the proposed scheme tends to be almost equivalent as that of sequentially operated RLS algorithm.

The rest of the paper is organized as follows: In Section 2, the system model for multipath based MIMO communication system is presented. In Section 3, the proposed LC-DDASP architecture is described. Complexity analysis and communication burden are described in Sections 4 and 5, respectively. The mean square error (MSE) performance is presented in Section 4, and Section 5 draws the conclusions.

2. System model

The block diagram of $N \times N$ MIMO communication system is shown in Figure 1. In MIMO communication system, the input signal is divided into N subblocks and then all the sublocks are transmitted separately through the use of multiple antennas. Due to the parallel interference [17] as shown in Figure 2, the received signal $\mathbf{y}_k$ can be expressed as

$$\mathbf{y}_k = \mathbf{H}_k^H \mathbf{x}_k + \boldsymbol{\vartheta}_k, \tag{1}$$

where

$$\mathbf{H}_k = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1N} \\ h_{21} & h_{22} & \cdots & h_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ h_{N1} & h_{N2} & \cdots & h_{NN} \end{bmatrix}$$

is $N \times N$ channel matrix, $\mathbf{x}_k = [x_{1,k}\ x_{2,k}\ \cdots\ x_{N,k}]^T$ is the transmitted signal vector and $\boldsymbol{\vartheta}_n = [\vartheta_{1,k}\ \vartheta_{2,k}\ \cdots\ \vartheta_{N,k}]^T$

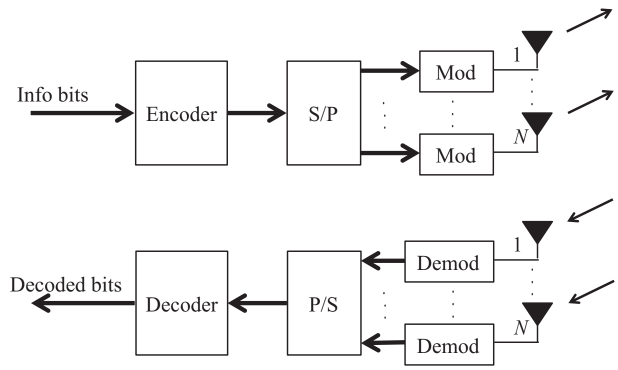

Figure 1. MIMO system model.

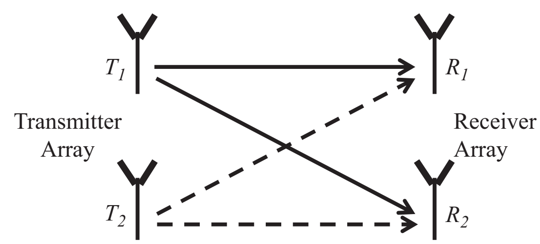

Figure 2. 2×2 MIMO communication system.

is the white noise with variance σ_{ϑ^2}. In case of diffused components, receiver induces a crucial impact on the size of the matrix. Therefore, the channel matrix $\widetilde{\mathbf{H}}_k$ becomes an $N \times N(C+1)$ matrix [18] that can be expressed as on the next page, where C shows the diffused components. The dimensions of $\widetilde{\mathbf{H}}_k$ are not only dependent on the number of antennas but it also depends upon the diffused components, as shown in Figure 3.

Furthermore, for multipath fading environment, $\mathbf{x}_k$ changes to $\widetilde{\mathbf{x}}_k = [x_{1,k} \cdots x_{1,k-(L-1)}\, x_{2,k} \cdots x_{2,k-(L-1)} \cdots x_{N,k-(L-1)}]^T$ which is a transmitted signal vector. The time other than the current time index k provides ISI.

3. Conventional PDASP architecture

The flow diagram of conventional PDASP architecture is shown in Figure 4. The PDASP architecture consists of four processing nodes, namely M_1, M_2, M_3 and M_4 which carry the information regarding error covariance matrix $\mathbf{\Psi}_k$, Kalman gain $\mathbf{g}_k$, error vector $\mathbf{e}_k$ and filter weights matrix $\mathbf{W}_k$, respectively. The processing nodes M_1 and M_4 are interlinked with M_2 and M_3, respectively. Likewise, the node M_2 is linked with M_1 and M_4 and the node M_3 is linked only with the node M_4. The PDASP architecture provides an average improvement of 94.97% in sense of decreased processing time then the sequential RLS algorithm. However, this improvement in decreased processing time is on behalf of high communication burden which provides time lag in the execution time of the adaptive filter [19]. Moreover, the communication burden varies for both the LoS and diffused components. In case of LoS communication, the dimensions of the filter weight matrix $\mathbf{W}_k$ and error covariance matrix $\mathbf{\Psi}_k$ are the same which implies the PDASP architecture follows the totally balancing communication procedure. In this procedure, first of all the update information of Kalman gain $\mathbf{g}_k$ is transmitted from node M_2 towards M_1 and M_4 then the nodes M_1 and M_4 capable to send the updated information of

$$\widetilde{\mathbf{H}}_k = \begin{bmatrix} h_{11(0)} & \cdots & h_{11(C)} & h_{21(0)} & \cdots & h_{N1(C)} \\ h_{12(0)} & \cdots & h_{12(C)} & h_{22(0)} & \cdots & h_{N2(C)} \\ \vdots & & \vdots & \vdots & \ddots & \vdots \\ h_{1N(0)} & \cdots & h_{1N(C)} & h_{2N(0)} & \cdots & h_{NN(C)} \end{bmatrix}$$

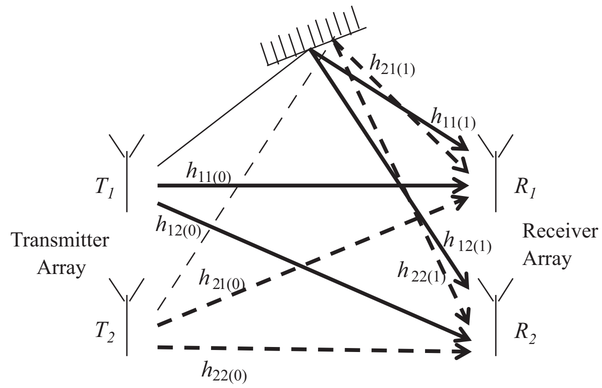

Figure 3. Frequency selective channel model for 2×2 MIMO communication system.

error covariance matrix $\mathbf{\Psi}_k$ and filter weight matrix $\mathbf{W}_k$ towards M_2 and M_3, respectively. Likewise, the nodes M_2 and M_3 send the information of $\mathbf{a}_k$ and $\mathbf{e}_k$ towards M_1 and M_4, respectively. However, in case of diffused components, the dimensions of filter weight matrix $\mathbf{W}_k$ and error covariance matrix $\mathbf{\Psi}_k$ are varies and depend upon the number of transmitting and receiving antennas as well as on the number of diffused components. The dimensions of error covariance matrix $\mathbf{\Psi}_k$, filter weight matrix $\mathbf{W}_k$ and Kalman gain $\mathbf{g}_k$ for 4×4 MIMO communication system with LoS and diffused components are shown in Table 1, where it can be visualized that the error covariance matrix $\mathbf{\Psi}_k$ may provides overwhelm transmission delay in the communication link as compared to the other elements. Furthermore, the per iteration PDASP based maximum communication burden for the transmission of data elements with LoS and diffused components is shown in Table 2. It can be seen that the communication burden provided by the PDASP architecture for diffused components provides a time lag on the execution time of adaptive algorithm.

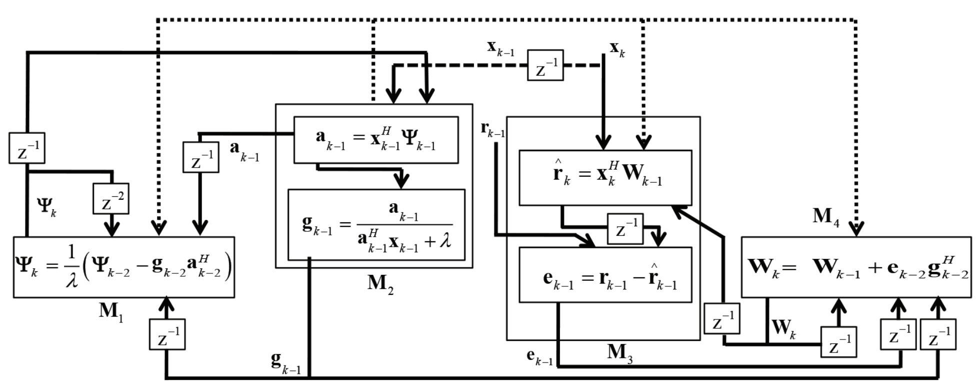

Figure 4. Implementation of MIMO RLS adaptive algorithm on PDASP architecture with nonaligned time indexes [14].

Table 1. Dimensions occupied by error covariance matrix, channel matrix and Kalman gain for 4×4 MIMO system with line-of-sight (LoS) and diffused components.

Diffused components	Error covariance matrix, $\mathbf{\Psi}_k$	Filter weight matrix, $\mathbf{W}_k$	Kalman gain, $\mathbf{g}_k$
L = 0	4×4	4×4	1×4
L = 1	8×8	4×8	1×8
L = 2	12×12	4×12	1×12
L = 3	16×16	4×16	1×16

Table 2. Maximum communication burden specified for one complete iteration with LoS and diffused components.

LoS/diffused components	2×2 MIMO	3×3 MIMO	4×4 MIMO
LoS component	10	18	24
One diffused component	28	54	88
Two diffused components	54	108	180

4. Proposed low complexity PDASP (LC-PDASP) architecture

In the proposed LC-PDASP architecture, each node uses the collaborative strategy though requires limited interaction with the other nodes in the distributed network. In this context, the individual computational complexity of all the nodes, $M_1 \cdots M_4$, in PDASP architecture is shown in Table 3; whereas, N shows the MIMO system order and L shows the diffused components. Fuethermore, in Table 3, it can be seen that the individual multiplication and addition complexity of the nodes M_1 and M_2 is greater than both the nodes M_3 and M_4, respectively. Therefore, if we combine the computational complexity of the nodes M_3 and M_4 that would be less or equal than the individual complexity of the nodes M_1 and M_2, respectively. Furthermore, it can be realized that multiplication complexity implies by the node M_1 is greater than all the other nodes in the PDASP architecture. Likewise, the error covariance matrix in node M_1 provides high communication burden as compared to the other nodes in the PDASP architecture which is clearly envisioned in Table 1. The communication burden provided by the error covariance matrix $\mathbf{\Psi}_k$ can be reduced by initializing the covariance matrix at node M_2 [12, 13]; therefore, for every iteration, the node M_2 uses the initialized error covariance matrix and finds the value of Kalman gain $\mathbf{g}_k$. In this way, the node M_1 has no need to operate in the distributed network. The flow diagram of the proposed LC-PDASP architecture is shown in Figure 5.

The proposed LC-PDASP architecture consists of only two low cost processing nodes, namely M_{12} and M_{34}, which are used for the complete communication setup. The processing node M_{12} carries the expression of Kalman gain; likewise, the node M_{34} carries the information regarding error vector and filter weight matrix. By using the nonaligned time indexes, the proposed LC-PDASP architecture runs in parallel fashion. Let the processing time taken by Kalman gain $\mathbf{g}_n$ and channel matrix $\mathbf{H}_n$ be $T_{\mathbf{g}}$ and $T_{\mathbf{H}}$, respectively. In case of diffused components, the computational cost provided by the node M_{12} is greater than the node M_{34}; therefore, the strict and sufficient condition in terms of low processing time can be written as

$$T_{\mathbf{H}} \ll T_{\mathbf{g}}. \tag{2}$$

Table 3. Individual node by node computational complexity of PDASP with diffused components.

	Node 1	Node 2	Node 3	Node 4
Multiplication complexity	$2(N+NL)^2$	$(N+NL)^2+$ $2N(L+1)$	$N^2(L+1)$	$N^2(L+1)$
2×2 with $L=1$	32	24	8	8
2×2 with $L=2$	72	48	12	12
3×3 with $L=1$	72	48	18	18
3×3 with $L=2$	162	99	27	27
Addition complexity	$(N+NL)^2$	$(N+NL)^2$	$N^2(L+1)$	$N^2(L+1)$
2×2 with $L=1$	16	16	8	8
2×2 with $L=2$	36	36	12	12
3×3 with $L=1$	36	36	18	18
3×3 with $L=2$	81	81	27	27

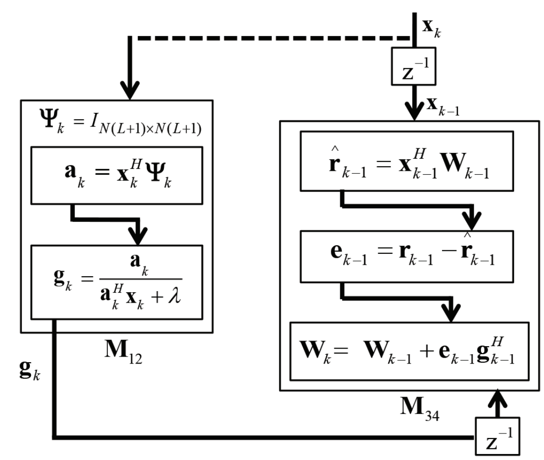

Figure 5. An RLS based proposed LC-PDASP architecture for MIMO communication system.

Likewise,

$$T_{\mathbf{g}} \ll T_{maxPDASP} \ll T_{seqRLS}, \tag{3}$$

where $T_{maxPDASP}$ is the maximum processing time taken by the conventional PDASP architecture and T_{seqRLS} is the time taken by the RLS algorithm when it operates sequentially.

5. Complexity analysis

In this section, the complexity analysis among the sequential RLS, PDASP and proposed LC-PDASP architecture is presented. The computational complexity of the sequential RLS algorithm requires $3(N+NC)^2 + 2N^2(C+1) + 2N(C+1) + 2$ multiplications and $2(N+NC)^2 + 2N^2(C+1)$ additions per iteration; where C shows the number of multipath components and N shows the dimensions of filter order. Furthermore, the conventional PDASP based RLS algorithm entiais $2(N+NC)^2$ multiplications/divisions and $(N+NC)^2$

additions/subtractions per iteration at maximum. On the other hand, RLS algorithm based on LC-PDASP architecture provides $(N+NC)^2+2N(C+1)$ multiplications/divisions and $(N+NC)^2$ additions/subtractions. The multiplication complexity comparisons among sequential RLS, PDASP and proposed LC-PDASP for $C=1$ and $C=2$ diffused components are shown in Figures 6 and 7, respectively. It can be seen that the proposed LC-PDASP architecture thus provides much lesser multiplication complexity than the conventional PDASP and sequential RLS algorithms.

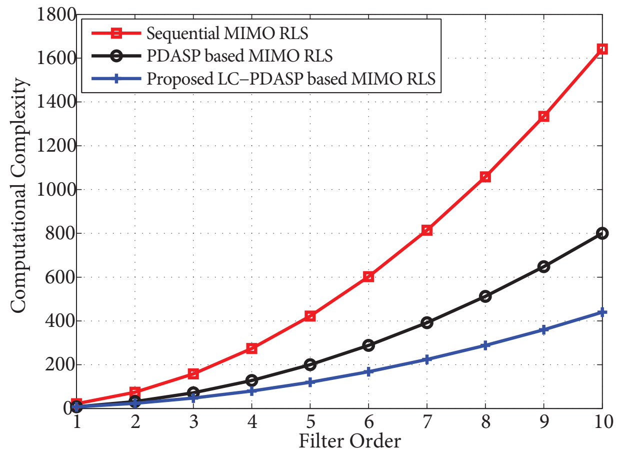

Figure 6. Multiplication complexity comparison among sequential and distributed techniques with one diffused component $(L=1)$.

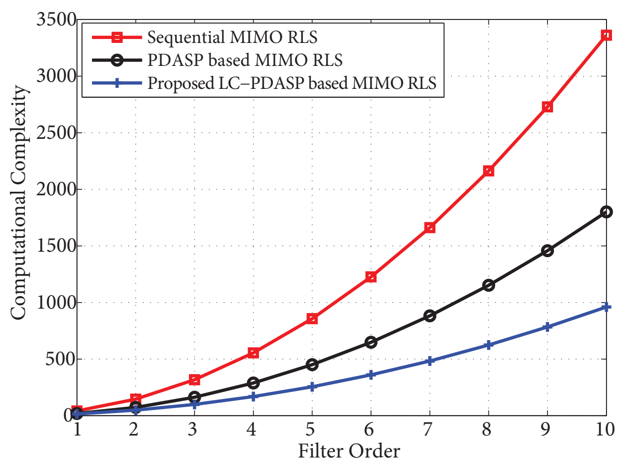

Figure 7. Multiplication complexity comparison among sequential and distributed techniques with two diffused components $(L=2)$.

6. Communication burden analysis

In this section, the communication burden analysis is presented. The communication burden provided by the proposed LC-PDASP technique is much lesser than the conventional PDASP architecture. The communication burden comparison for different MIMO systems with diffused components is shown in Table 4. It can be observed that LC-PDASP architecture entails $N(C+1)$ communication load; where N shows the MIMO system order and L shows the number of diffused components. Furthermore, the proposed scheme provides an improvement of more than of 85% in sense of decreased communication burden which provides a significant impact on the overall execution time of the algorithm.

Table 4. Communication burden comparison between conventional PDASP and proposed LC-PDASP architectures with diffused components (DCs).

System order	Conventional PDASP	Proposed LC-PDASP	% difference
2×2 MIMO with $L = 1$	28	4	85.71%
2×2 MIMO with $L = 2$	54	6	88.88%
3×3 MIMO with $L = 1$	54	6	88.88%
3×3 MIMO with $L = 2$	108	9	91.66%
4×4 MIMO with $L = 1$t	88	8	90.90%
4×4 MIMO with $L = 2$	180	12	93.33%

7. Mean square performance

The Monte Carlo simulations are performed on 4×4 MIMO communications system with binary phase shift keying (BPSK). The forgetting parameter λ is set as 0.98 for all the simulation setup. The MSE of MIMO RLS based proposed LC-PDASP technique is then compared with conventional PDASP architecture and sequential RLS algorithm. Figures 8 and 9 show the MSE comparison at low and high doppler rate, respectively. It can be seen that the convergence performance of the proposed LC-PDASP technique tends to be almost same as that of sequential RLS algorithm. This improved performance of the proposed technique for both the low and high doppler rates is due to the less involvement of time nonalignments as compared to the PDASP architecture.

8. Conclusion

In this paper, a new MIMO RLS based proposed LC-PDASP architecture for a group of computationally incapable and incapable small platforms has been proposed. The proposed architecture with the implementation of MIMO RLS algorithm has been capable to run computationally expensive procedures parallely. The proposed LC-PDASP architecture uses collaborative strategy though requires limited interaction with other nodes in the distributed network. It has been observed that MIMO RLS based the proposed LC-PDASP architecture entails lesser multiplication/division complexity as compared to PDASP and sequentially operated RLS algorithms. Furthermore, the communication burden which has been provided by the proposed LC-PDASP architecture is much lesser than the PDASP architecture. Moreover, the mean square error (MSE) provided by the proposed architecture tends to be the lesser and almost same as compared to PDASP and sequential RLS algorithms, respectively.

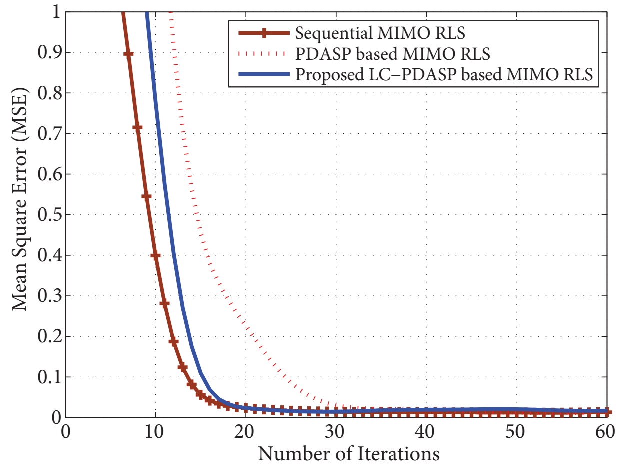

Figure 8. Mean square error (MSE) performance for 4×4 MIMO communication system when $f_D T = 10^{-6}$.

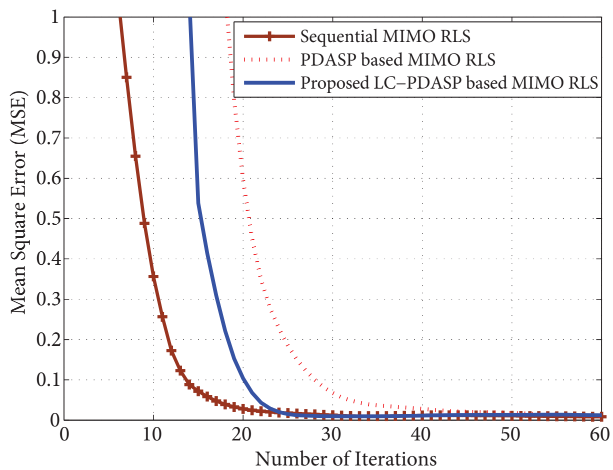

Figure 9. Mean square error (MSE) performance for 4×4 MIMO communication system when $f_D T = 10^{-3}$.

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