Non-stationary Sparse Fading Channel Estimation for Next Generation Mobile Systems

Saadat Dehgan[1], Changiz Ghobadi[1], Javad Nourinia[1], Jie Yang[2], Guan Gui[2*] and Ehsan Mostafapour[1]
[1] Department of Electrical Engineering, Urmia University, Urmia, Iran
[saadat.dgolshan70@gmail.com, ch.ghobadi@urmia.ac.ir, j.nourinia@urmia.ac.ir, ehsan_mostafapour@yahoo.com]
[2] College of Telecom and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing, China
[jyang@njupt.edu.cn, guiguan@njupt.edu.cn]
*Corresponding author: Guan Gui

Received August 9, 2017; revised September 21, 2017; accepted October 8, 2017; published March 31, 2018

Abstract

In this paper the problem of massive multiple input multiple output (MIMO) channel estimation with sparsity aware adaptive algorithms for 5th generation mobile systems is investigated. These channels are shown to be non-stationary along with being sparse. Non-stationarity is a feature that implies channel taps change with time. Up until now most of the adaptive algorithms that have been presented for channel estimation, have only considered sparsity and very few of them have been tested in non-stationary conditions. Therefore we investigate the performance of several newly proposed sparsity aware algorithms in these conditions and finally propose an enhanced version of RZA-LMS/F algorithm with variable threshold namely VT-RZA-LMS/F. The results show that this algorithm has better performance than all other algorithms for the next generation channel estimation problems, especially when the non-stationarity gets high. Overall, in this paper for the first time, we estimate a non-stationary Rayleigh fading channel with sparsity aware algorithms and show that by increasing non-stationarity, the estimation performance declines.

Keywords: Channel estimation; Sparse; Non-stationary; Adaptive algorithms; Variable threshold.

This research was supported by National Natural Science Foundation of China grants (No. 61401069, No. 61271240, No. 61501254), Jiangsu Specially Appointed Professor Grant (RK002STP16001), High-level talent startup grant of Nanjing University of Posts and Telecommunications (XK0010915026) and “1311 Talent Plan” of Nanjing University of Posts and Telecommunications.

http://doi.org/10.3837/tiis.2018.03.004 **ISSN : 1976-7277**

1. Introduction

Channel estimation is a necessary part of every modern communication system [1]–[6]. In this task the aim is to estimate the taps of an unknown channel vector that can be modeled with various features. If a large number of the channel weigh vector entries are zero, and only a few of these entries have non-zero values, we call this as sparse channel [7]–[11].

In several papers including [12]–[16] the estimation of a sparse channel have been mentioned. However, a more detailed definition of channel model is needed for precise evaluation of channel estimation algorithms and methods. Wireless communication channels are usually realized with fading models due to the presence of multiple scatters. Some of these fading channel models are non-stationary [17][18]. This means that the values and statistical characteristics of their weights vary with time.

Newly immerging 5th generation (5G) [19]–[23] mobile platforms are known to use multiple input multiple output (MIMO) system in order to increase the costumer bandwidth dramatically. In these systems all users utilize several antennas to send and receive data from a massive MIMO base station. The channels appointed to these systems have two important features that are described as follows: The first feature is sparsity. Channels in massive MIMO systems are sparse due large channel bandwidths [19], [24], [25]. The second feature is non-stationarity. Measurement of vehicle-to-vehicle channels has proved that the stationary gap of channels between vehicles driving in opposite directions can be very short especially when they use MIMO antenna systems. Therefore, research of non-stationary channel modeling has gradually become a hot research topic especially for high-mobility scenarios that are expected to be typical scenarios for the 5G wireless communication systems. It can be concluded that the channels of 5G mobile systems are both sparse and non-stationary. Therefore we need to design and present algorithms that can handle sparsity and non-stationarity at the same time.

Although there have been considerable effort in designing and testing new adaptive algorithms for sparse channel estimation and sparse system identification, very few researchers [26] have considered non-stationarity along with sparsity. Thus, the search for a suitable algorithm that is resilient to both sparsity and non-stationarity is still on. In order to explain the course of evolution for our proposed algorithm, here we briefly survey some of recently proposed sparsity aware algorithms.

First of all the zero-attracting LMS (ZA-LMS) and reweighted ZA-LMS (RZA-LMS) algorithms had been proposed in [27] specially for sparse system identification and from that time, almost all newly presented sparsity aware algorithms have shared the penalty terms of these algorithms. Next in [28] the normalized versions of these algorithms namely ZA-NLMS and RZA-NLMS have been investigated and they had reasonable results in sparse system identification considering their higher complexity in comparison with non-normalized versions. The authors of [29][30] have introduced sparsity aware least mean square (LMF) algorithm to sparse system identification by adding l_1 norm penalty to its cost function. In [31] the sparsity aware version of least-mean mixture-norm (LMMN) algorithm has been presented. Next in [14][30][32] the least mean square/fourth (LMS/F) algorithm has been used in sparse channel estimation. Finally, Correntropy-induced metric based least-mean mixture-norm LMMN (CIM-LMMN) algorithm [33] and the soft parameter function penalized normalized maximum correntropy criterion (SPF-NMCC) algorithm [34] have been presented that had better performance in sparse system identification in comparison with the family of LMS/F algorithms with the cost of more computational complexity. All of these algorithms have great performances for sparse systems, but none of these algorithms have been specially designed for non-stationary channel estimation. Therefore we searched the literature of adaptive algorithms and found that in [35] a variable threshold LMS/F (VT-LMS/F) algorithm had been proposed that had better performance in non-stationary conditions. By applying sparsity constrain to its cost function 2 new sparsity and non-stationarity aware algorithms namely VT-ZA-LMS/F and VT-RZA-LMS/F are proposed in this paper. Our simulations showed a better performance with these algorithms for 5th generation non-stationary channel estimation.

The remainder of this paper is organized as follows: Section II introduces the methodology of modelling sparse fading channels. In Section III some relations of previously presented algorithms are surveyed in order to present our proposed algorithms. In section IV the thorough simulation results are presented for different levels of sparsity and non-stationarity. Finally, the conclusion is given in Section V.

2. Problem Statement

As mentioned in the introduction part, the non-stationarity have not been considered in recently published channel estimation papers and only sparsity have been studied. However, for modeling a 5G wireless channel both of these features are needed. For a channel to be non-stationary, its producing model must be time varying. Therefore, the desired tap weights of our simulations in this paper are produced according to the non-stationary Clarke's model for Rayleigh fading [17] with the following relation:

$$h(t) = \frac{1}{\sqrt{K}} \sum_{k=1}^{K} \exp[j(2\pi f_d t cos\alpha_k + \phi_k)] \tag{1}$$

where K is the number of propagation paths, f_d is the maximum Doppler frequency (that represents the relative speed of transmitter and receiver) and α_k and ϕ_k are the angle of arrival and initial phase of kth propagation path, respectively. Both of these angles are uniformly distributed over $[-\pi, \pi)$ for all k and they are mutually independent. For discretization, it is suggested to replace t with nT_s, where T_s is the sampling period. At each instant, we insert discrete values of this non-stationary fading model to the sparse channel vector $\boldsymbol{h}(n)$ and therefore a non-stationary sparse channel vector is obtained with a few non-zero and time varying elements.

$$\boldsymbol{h}(n) = [h_0(n)\ 0\ 0\ 0\ 0 \ldots\ h_i(n)\ 0\ 0\ 0 \ldots\ h_{M-1}(n)]' \tag{2}$$

where M is the size of channel vector. The probability distribution function (PDF) of non-zero channel coefficients of this vector follows a Rayleigh model as in **Fig. 1.**

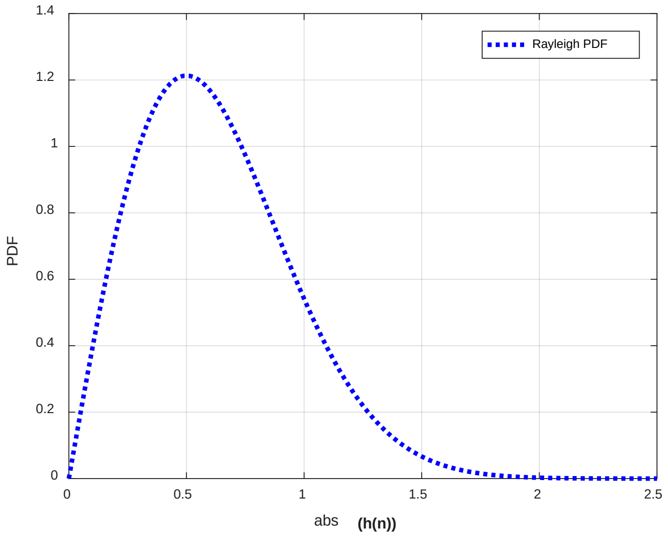

Fig. 1. PDF of non-zero channel coefficients.

The degree of non-stationarity of this channel vector is determined by the values of Doppler frequency and sampling period. It can be expected that as the degree of non-stationarity gets higher and the channel vector changes more rapidly in time, the estimation performance of adaptive algorithms to track this channel degrade. Our purpose is to estimate the time varying $\boldsymbol{h}(n)$ vector using the noisy observations $d(n)$ and input vector $\boldsymbol{x}(n)$ that relate to each other using the following relation:

$$d(n) = \boldsymbol{h}^T(n)\boldsymbol{x}(n) + z(n) \tag{3}$$

where $z(n)$ is the plant noise that is assumed to be Gaussian with zero mean and variance of σ_n^2. This can be seen in **Fig. 2.**

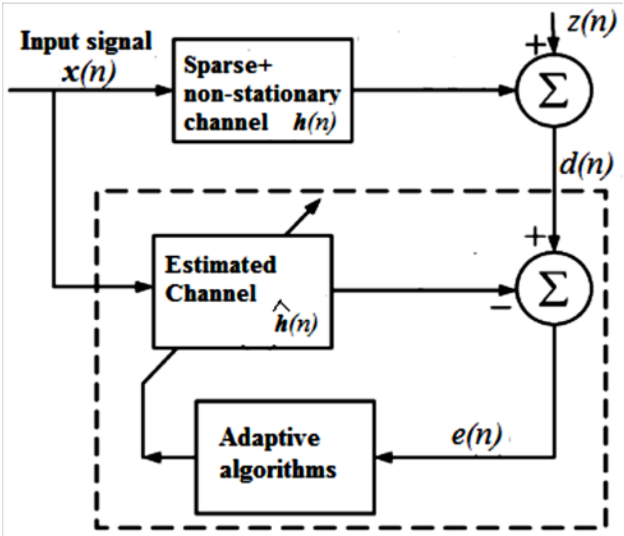

Fig. 2. Sparse+non-stationary channel estimation with adaptive algorithms.

In order to evaluate the performance of adaptive filters in tracking the non-stationary and time varying channel weights an appropriate error criteria must be used that depends on the differences between actual and estimated weights. For this reason in this paper, the performance evaluation is based on the Mean Square Deviation (MSD) criteria given by:

$$\text{Average } MSD\left\{\widehat{\boldsymbol{h}}(n)\right\} = \mathbb{E}\left\{\left\|\boldsymbol{h}(\boldsymbol{n}) - \widehat{\boldsymbol{h}}(n)\right\|^2\right\} \tag{4}$$

where $\mathbb{E}\{\cdot\}$ denotes statistical expectation and $\|.\|^2$ is used for showing Euclidean norm. It is important to mention that in this paper for the first time, the estimation of a non-stationary Rayleigh fading channel with sparsity aware algorithms is performed and the results are going to show that by increasing non-stationarity, the estimation performance declines.

3. Our Proposed Algorithms

As mentioned earlier, in this paper we only considered the family of LMS/F algorithms because of their reasonable performance and low computational complexity. The traditional LMS/F algorithm have been designed with respect to least mean square and forth criterion and the updating relation of this algorithm can be given as:

$$\widehat{\boldsymbol{h}}(n+1) = \widehat{\boldsymbol{h}}(n) + \mu \boldsymbol{x}^T(n)\frac{e^3(n)}{e^2(n)+V_{th}} \tag{5}$$

where $\widehat{\boldsymbol{h}}(n) = \left[\hat{h}_0(n),\ \ldots, \hat{h}_i(n), \ldots, \hat{h}_{M-1}(n)\ \right]^T$ is the estimated vector by proposed algorithms, $e(n)$ is the error and V_{th} is a treshold value. The LMS/F algorithm enjoys the overall advantages of LMS and LMF algorithms and it has been shown to have better performance than both of these algorithms. But in spite of this fact, the LMS/F algorithm has not been specially designed for non-stationary systems.

In [35] a new version of LMS/F algorithm is proposed with variable threshold and it was proven to be robust against non-stationary systems. The update relation of this variable threshold LMS/F (VT-LMS/F) algorithm is:

$$\widehat{\boldsymbol{h}}(n+1) = \widehat{\boldsymbol{h}}(n) + \mu \boldsymbol{x}^T(n)\frac{e^3(n)}{e^2(n)+V_{th}(n)} \tag{6}$$

where the threshold is time varying like the system weights and it can be obtained at each step using the following relation:

$$\sigma(n+1) = \lambda\sigma(n) + (1-\lambda)|e(n)| \tag{7}$$

$$V_{th}(n+1) = 5(\sigma(n+1))^2 \tag{8}$$

where $\lambda$is a constant set to 0.9995 in our simulations. Other parameters of this algorithm are determined using tryouts in the simulation part. The argument for choosing these update relations is that LMS algorithm has been shown to have a reasonable misadjustment performance in non-stationary variable tracking [35]. For LMS/F algorithm to have a similar performance as LMS, we must select $V_{th} = 5\mathbb{E}\{\sigma_n^2\}$, but as we do not have any prior knowledge about the plant noise $z(n)$, the IIR estimated value of $5\mathbb{E}\{|e(n)|\}^2$ is considered to be a way to approximate $5\mathbb{E}\{\sigma_n^2\}$. In equations (7) and (8), $\sigma(n)$ is the standard IIR estimator for $\mathbb{E}\{|e(n)|\}$.

3.1 ZA-LMS/F Algorithm

For an algorithm to be sparsity aware and converge faster to sparse systems, a zero attracting penalty term must be added to it [27]. The ZA-LMS/F algorithm has been constructed by introducing the l_1 norm of the weight vector to the cost function of LMS/F algorithm in [30]:

$$G_{ZA-LMS/F}(n) = \frac{1}{2}e^2(n) - \frac{1}{2}V_{th}\ln(e^2(n) + V_{th}) + \rho_{ZA}\left\|\hat{\boldsymbol{h}}(n)\right\|_1 \quad (9)$$

where ρ_{ZA} is a regularization parameter and $\|.\|_1$ denotes l_1 norm operation. The update relation of ZA-LMS/F algorithm is given by:

$$\hat{\boldsymbol{h}}(n+1) = \hat{\boldsymbol{h}}(n) + \mu\frac{\partial G_{ZA-LMS/F}(n)}{\partial\hat{\boldsymbol{h}}(n)} = \hat{\boldsymbol{h}}(n) + \mu\frac{e^3(n)\boldsymbol{x}(n)}{e^2(n)+V_{th}} + \gamma_{ZA}sgn\left(\hat{\boldsymbol{h}}(n)\right) \quad (10)$$

where $\gamma_{ZA} = \mu\rho_{ZA}$ and the $sgn(.)$ function is given by:

$$sgn\left(\hat{\boldsymbol{h}}(n)\right) = \begin{cases} 1, & \hat{h}_i(n) > 0 \\ 0, & \hat{h}_i(n) = 0 \\ -1, & \hat{h}_i(n) < 0 \end{cases} \quad (11)$$

Here it is useful to compare the update relation of ZA-LMS/F algorithm with that of simple ZA-LMS algorithm which is used and compared in the channel estimation simulations of this paper:

$$\hat{\boldsymbol{h}}(n+1) = \hat{\boldsymbol{h}}(n) + \mu\frac{\partial G_{ZA-LMS}(n)}{\partial\hat{\boldsymbol{h}}(n)} = \hat{\boldsymbol{h}}(n) + \mu e(n)x(n) + \gamma_{ZA}sgn\left(\hat{\boldsymbol{h}}(n)\right) \quad (12)$$

Notice the difference between the powers of $e(n)$ in these two algorithms.

3.2 RZA-LMS/F

In order to improve the sparsity awareness in comparison with ZA-LMS/F algorithm, the RZA-LMS/F algorithm has been introduced by the following cost function:

$$G_{RZA-LMS/F}(n) = \frac{1}{2}e^2(n) - \frac{1}{2}V_{th}\ln(e^2(n) + V_{th}) + \rho_{RZA}\sum_{i=0}^{N-1} log\left(1 + \left|\hat{\boldsymbol{h}}(n)\right|/\varepsilon\right) \quad (13)$$

The update relation of this algorithm is given by:

$$\hat{\boldsymbol{h}}(n+1) = \hat{\boldsymbol{h}}(n) + \mu\frac{\partial G_{RZA-LMS/F}(n)}{\partial\hat{\boldsymbol{h}}(n)} = \hat{\boldsymbol{h}}(n) + \mu\frac{e^3(n)\boldsymbol{x}(n)}{e^2(n)+V_{th}} + \gamma_{RZA}\frac{sgn\left(\hat{\boldsymbol{h}}(n)\right)}{1+\varepsilon\left|\hat{\boldsymbol{h}}(n)\right|} \quad (14)$$

where $\gamma_{RZA} = \mu\rho_{RZA}/\varepsilon$ and ε is the shrinkage control parameter. If a coefficient of system or channel vector is close to $1/\varepsilon$, the zero attracting effect is high on this coefficient. However, if $|h_i(n)| \gg 1/\varepsilon$ the zero attraction will have a lesser effect on this coefficient. Again, the update function of RZA-LMS/F algorithm is compared with that of simple RZA-LMS in order to confirm the differences:

$$\hat{\boldsymbol{h}}(n+1) = \hat{\boldsymbol{h}}(n) + \mu\frac{\partial G_{RZA-LMS}(n)}{\partial\hat{\boldsymbol{h}}(n)} = \hat{\boldsymbol{h}}(n) + \mu e(n)x(n) + \gamma_{RZA}\frac{sgn\left(\hat{\boldsymbol{h}}(n)\right)}{1+\varepsilon\left|\hat{\boldsymbol{h}}(n)\right|} \quad (15)$$

Both ZA-LMS/F and RZA-LMS/F algorithms have been shown to have better performances than their LMS counterparts do in [36].

3.3 Our proposed algorithms

For the non-stationary case, it is necessary to adjust the V_{th} parameter according to the variations of the unknown 5G channel vector. All of other adjustments of parameters have been taken into the consideration for RZA-LMS/F and ZA-LMS/F algorithms in [36]. Our contribution in this paper is to design an algorithm that is powerful against channel

non-stationarities along with sparsity. Here our proposed algorithms are given by replacing V_{th} with $V_{th}(n)$:
First the Variable Threshold ZA-LMS/F (VT-ZA-LMS/F) algorithm is presented with update relation as:

$$\hat{\boldsymbol{h}}(n+1) = \hat{\boldsymbol{h}}(n) + \mu \frac{e^3(n)\boldsymbol{x}(n)}{e^2(n)+V_{th}(n)} + \gamma_{ZA} sgn\left(\hat{\boldsymbol{h}}(n)\right) \tag{16}$$

The second proposed algorithm is the Variable threshold RZA-LMS/F (VT-RZA-LMS/F) algorithm with update relation as:

$$\hat{\boldsymbol{h}}(n+1) = \hat{\boldsymbol{h}}(n) + \mu \frac{e^3(n)\boldsymbol{x}(n)}{e^2(n)+V_{th}(n)} + \gamma_{RZA} \frac{sgn\left(\hat{\boldsymbol{h}}(n)\right)}{1+\varepsilon\left|\hat{\boldsymbol{h}}(n)\right|} \tag{17}$$

In both of these algorithms $V_{th}(n)$ is obtained using (7) and (8). These two algorithms are both robust to channel sparsity and non-stationarity of 5G systems. In simulation part it is shown that the convergence rate of these algorithms are higher than all recently proposed algorithms. In order to show the superiority of these algorithms, we changed the degree of non-stationarity in our simulations and showed that for highly non-stationary channels, the estimation performances of our proposed algorithms become more significant.

3.4 Computational complexity analysis

In order to prove the eligibility of proposed algorithms, their computational complexity must be compared with other introduced sparsity aware algorithms. It can be expected that for more advanced algorithms (like variable threshold algorithms with extra threshold adjustment relations), the computational complexity becomes higher, but it is important to show that this raise in complexity reconcile with higher performance. It is commonplace [34] to present complexity with respect to the size of unknown sparse vector (M) and the number of non-zero elements of this vector (K). The complexity of analyzed algorithms in this paper are given in **Table 1**.

Table 1. The computational complexity of introduced adaptive algorithms

algorithms	Additions	Multiplications	Divisions
LMS	2M	2M+1	-
ZA-LMS	M+3K	M+3K+1	-
RZA-LMS	M+4K	M+4K+1	M
LMS/F	2M+1	2M+4	1
ZA- LMS/F	M+3K+1	M+3K+3	1
RZA- LMS/F	M+4K+1	M+4K+4	M+1
VT-LMS/F	2M+3	2M+8	1
VT-ZA- LMS/F	M+3K+3	M+3K+7	1
VT-RZA- LMS/F	M+4K+3	M+4K+8	M+1

As it can be seen, the computational complexity of our proposed variable threshold algorithms are slightly higher than their fixed threshold counterparts, but in simulation part it will be shown that this raise in computational complexity results in noticeable performance improvements in non-stationary cases.

4. Simulation Results

Here our simulation results are given, but first the numerical values of constants in the analyzed algorithms are presented. The step size μ for all algorithms is considered to be between 0.014 and 0.017. The λ parameter in (7) is set to 0.9995. ρ_{ZA} is equal to 0.0004 and ρ_{RZA} is 0.04. Also $\varepsilon = 10$. The Doppler frequency shift is assumed to be between 10-30 Hz. In addition, sampling period considered between 10^{-6} to 10^{-3} seconds. It should be noted that as these two values get higher, the degree of non-stationarity increases and therefore the convergence of algorithms accompany ripples. All given results are averaged through 20 simulations. This averaging can make smoother curves for error performances. However, for non-stationary case, the averaging cannot eliminate the aforementioned ripples.

First, the performance of several algorithms including our proposed variable threshold schemes is compared in estimating a weakly non-stationary (or almost stationary) Rayleigh fading channel. In order to produce the sparse, time varying channel a 16×3000 matrix is considered. Only the first and third rows of this matrix are considered to be occupied with Rayleigh channel values that are produced using (1). At each iteration, only one column of this matrix is inserted to assumed algorithm. The values of T_s and f_d are 10^{-6} Hz and 10 Sec, respectively. In this case, the amplitude of channel weights in the first and third row, change very slowly through the simulation iterations as in **Fig. 3**.

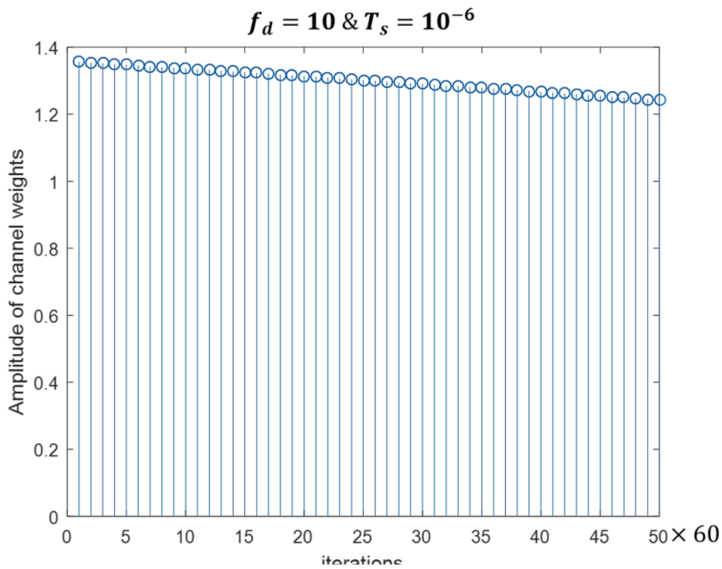

Fig. 3. The change of non-zero weight amplitudes through 3000 iterations for weakly non-stationary case.

The performance of analyzed algorithms in this condition is given in **Fig. 4**. In this Figure, we sampled error values in 3000 iterations and only presented the results at each 200 iterations. In this case, only 11 samples are presented. The cause of this sampling is firstly because of the distinguishability of algorithm performances and secondly because of channel non-stationarity which is clearer in **Fig. 7**.

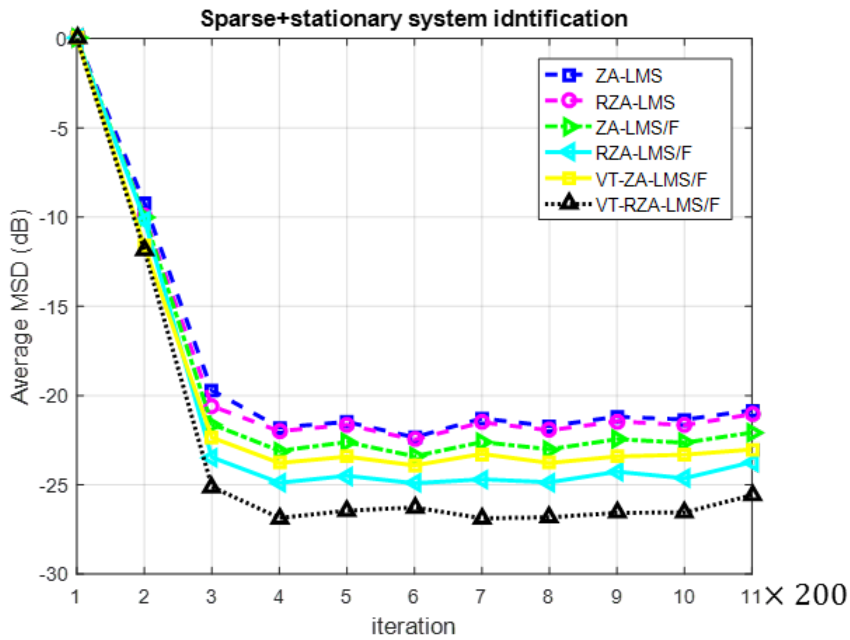

Fig. 4. Sampled performance comparison of various algorithms in estimating a weakly non-stationary sparse channel.

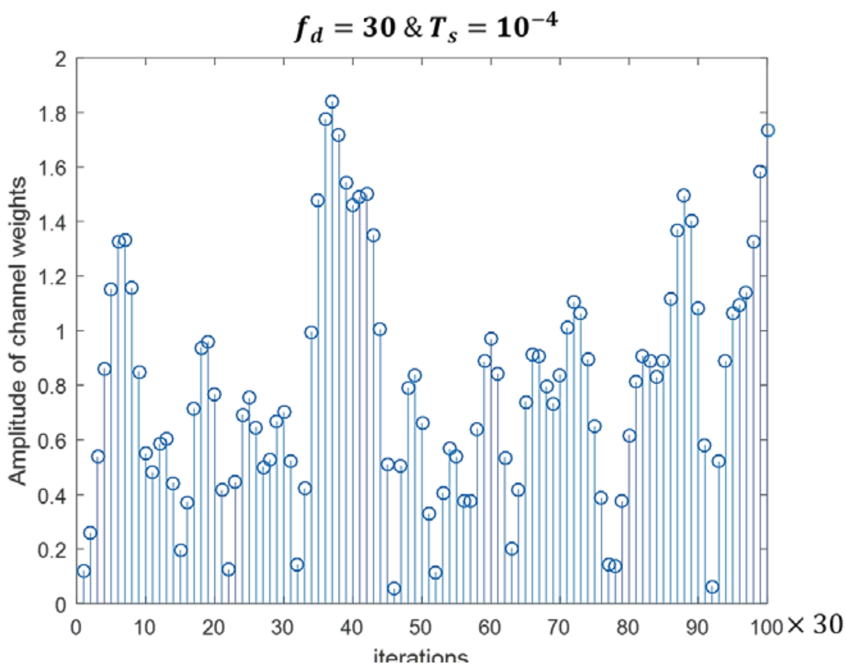

Fig. 5. The change of non-zero weight amplitudes through 3000 iterations for highly non-stationary case.

It can be seen that the performance of RZA-LMS/F algorithm is better than VT-ZA-LMS/F in weakly non-stationary and sparse channel estimation and VT-RZA-LMS/F algorithm prevails all considered algorithms.
Secondly the non-stationarity value is raised to show the performance degradation of highly time varying channels. For this case, the values of T_s and f_d are assumed to be 10^{-4} Hz and 30 Sec, respectively. In this case, the channel weights in the first and third row change rapidly through iterations (like in a true 5G system) and this is shown in **Fig. 5**.

The performance on this highly non-stationary scenario where f_d is equal to 30 Hz and T_s is 10^{-4} Sec, is presented in **Fig. 6**. Again, we sampled error values at each 200 iterations and only presented the results for 11 points. The performance degradation off all algorithms should be noted in this case.

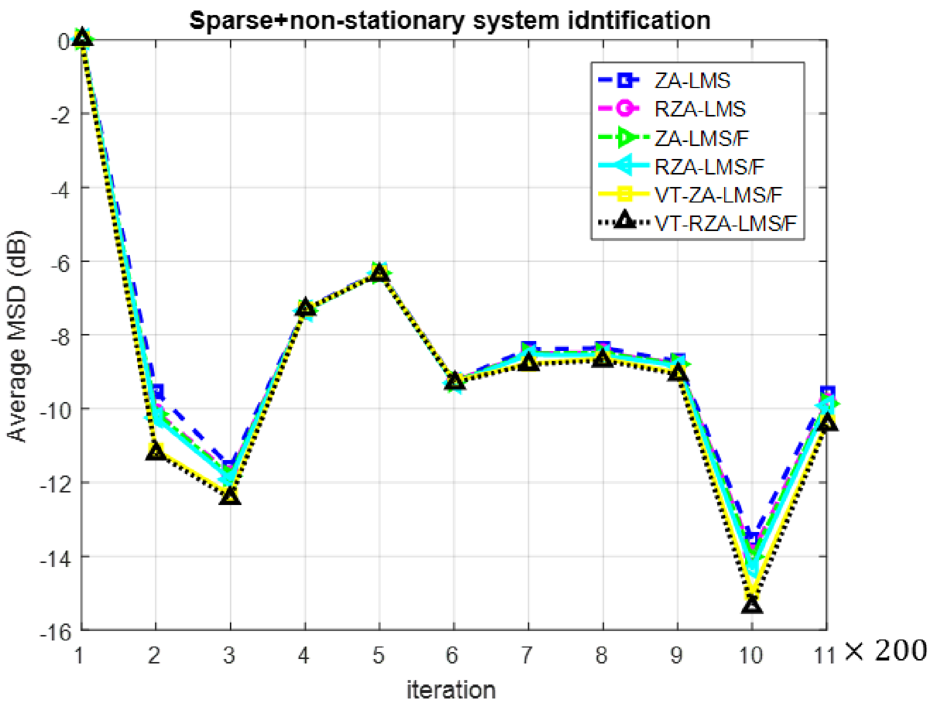

Fig. 6. Sampled performance comparison of various algorithms in estimating a highly non-stationary sparse channel.

When the non-stationarity rises, the performance of VT-ZA-LMS/F gets better than RZA-LMS/F algorithm that is not designed for this condition. Here in **Fig. 7**, the results without sampling of error values are presented in all iterations for showing the effect of rapid channel changes on the performance of adaptive filters. It is important to mention that the presented replicas cannot be deleted by averaging several simulations because the produced ripples are intrinsic to the channel.

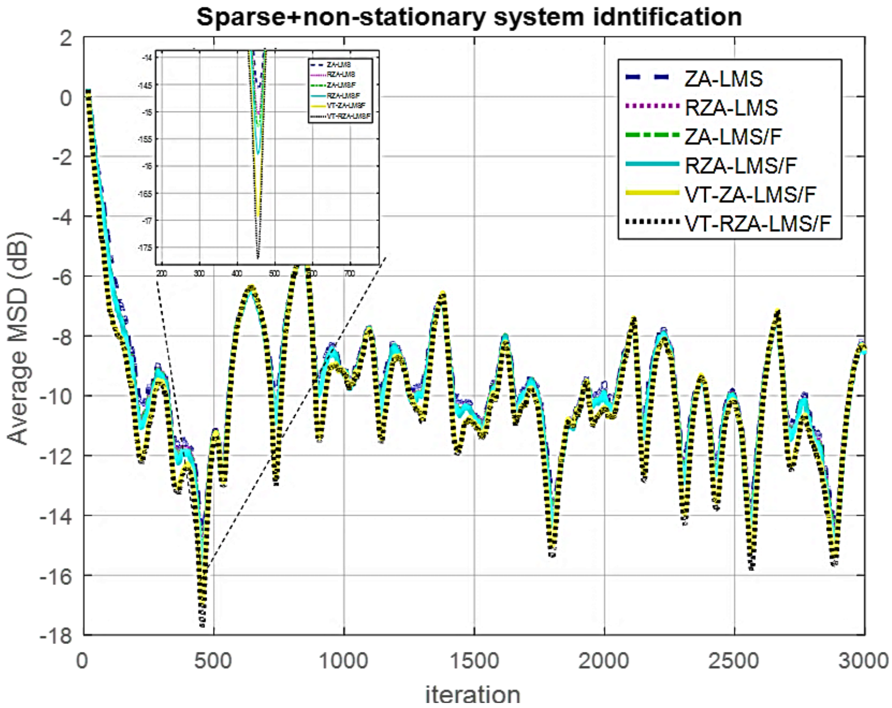

Fig. 7. Performance comparison of various algorithms in estimating a highly non-stationary sparse channel for 3000 iterations.

Finally, the results of our last simulation is presented in **Fig. 8**. In this simulation, we change the level of sparsity (which may happen in a 5G system) in a highly non-stationary case ($f_d = 30$ Hz and $T_s = 10^{-4}$ Sec) in order to show the superiority of presented algorithms. This simulation consists of 1800 iterations, in the first 600 iterations it is assumed that only one row of channel matrix have values and changes with time (highly sparse). In the second 600 iterations, it is assumed that 3 rows of 16 rows have non-stationary values. In addition, in the third 600 iterations, it is assumed that all even rows of the channel matrix have values (weakly sparse). As we can see in **Fig. 8**, it is important to mention that as the number of non-zero rows grow, the performance of algorithms degrade because they need to track more non-stationary channel values. Also as the system is highly non-stationary the performances of variable threshold algorithms are better in all 3 cases.

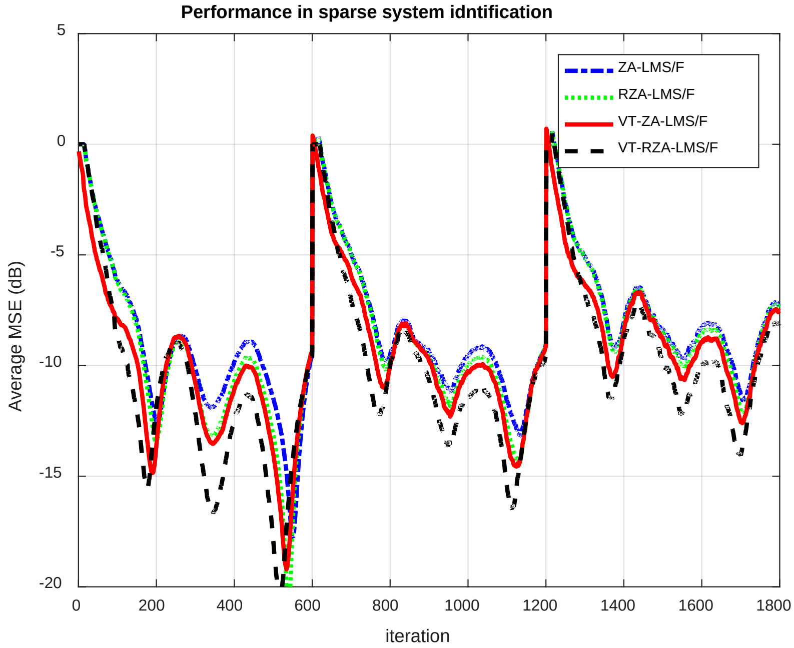

Fig. 8. Performance comparison of various algorithms in estimation of a channel with variable sparsity and non-stationarity.

5. Conclusion

In this paper, we showed that the non-stationarity is an important feature of channels in 5th generation mobile systems along with sparsity that can degrade their estimation performance with adaptive algorithms. Therefore, in this paper we modeled a sparse Rayleigh fading channel and proposed two enhanced versions of sparsity aware LMS/F algorithm family namely, variable threshold RZA-LMS/F and variable threshold ZA-LMS/F to improve non-stationary channel estimation performance. The robustness of proposed algorithms were tested in several simulations with different levels of sparsity and non-stationarity and the results showed that in all conditions, the VT-RZA-LMS/F algorithm is a reliable choice. In future works we will test new sparsity aware variable step-size adaptive algorithms in non-stationary channel estimation in order to find other suitable choices for this task.

References

[1] J. Zhang, G. Liu, F. Zhang, L. Tian, N. Sheng, and P. Zhang, "Emerging Challenges to IMT-Advanced Channel Model," *IEEE Veh. Technol. Mag.*, vol. 6, no. 2, pp. 92–100, 2011. Article (CrossRef Link)

[2] J. Zhang, D. Dong, Y. Liang, C. Huang, and G. Liu, "Propagation Characteristics of Wideband Relay Channels in Urban Micro-Cell Environment," *IEEE Antennas Wirel. Propag. Lett.*, vol. 9, pp. 657–661, 2010. Article (CrossRef Link)

[3] J. Zhang, Y. Zhang, Y. Yu, R. Xu, Q. Zheng, and P. Zhang, "3-D MIMO : How Much Does It Meet Our Expectations Observed From Channel Measurements?," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 8, pp. 1887–1903, 2017. Article (CrossRef Link)

[4] J. Zhang, "The Interdisciplinary Research of Big Data and Wireless Channel: A Cluster-Nuclei Based Channel Model," *China Commun.*, vol. 13, no. 2, pp. 14–26, 2016. Article (CrossRef Link)

[5] R. Cao, F. Gao, and X. Zhang, "An Angular Parameter Estimation Method for Incoherently Distributed Sources Via," *IEEE Trans. Signal Process.*, vol. 64, no. 17, pp. 4493–4503, 2016. Article (CrossRef Link)

[6] F. Gao, R. Zhang, and Y.-C. Liang, "Channel Estimation for OFDM Modulated Two-Way Relay Networks," *IEEE Trans. Signal Process.*, vol. 57, no. 11, pp. 4443–4455, 2009. Article (CrossRef Link)

[7] W. Ma, H. Qu, G. Gui, L. Xu, J. Zhao, and B. Chen, "Maximum correntropy criterion based sparse adaptive filtering algorithms for robust channel estimation under non-Gaussian environments," *J. Franklin Inst.*, vol. 352, no. 7, pp. 2708–2727, 2015. Article (CrossRef Link)

[8] L. Dai, Z. Wang, and Z. Yang, "Compressive sensing based time domain synchronous OFDM transmission for vehicular communications," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 9, pp. 460–469, 2013. Article (CrossRef Link)

[9] L. Dai, Z. Wang, Z. Yang, G. Gui, and F. Adachi, "Reliable and energy-efficient OFDM based on structured compressive sensing," in *Proc. of IEEE International Conference on Communications (ICC), Sydney, Australia*, 10-14 June 2014, 2014, pp. 1–6. Article (CrossRef Link)

[10] J. Kivinen, P. Suvikunnas, L. Vuokko, and P. Vainikainen, "Experimental investigations of MIMO propagation channels," *IEEE Antennas Propag. Soc. Int. Symp. (IEEE Cat. No.02CH37313)*, vol. 3, pp. 206–209, 2002. Article (CrossRef Link)

[11] J. Zhang, C. Pan, F. Pei, G. Liu, and X. Cheng, "Three-Dimensional Fading Channel Models: A Survey of Elevation Angle Research," *China Commun.*, vol. 52, no. 6, pp. 218–226, 2014. Article (CrossRef Link)

[12] G. Gui and F. Adachi, "Improved least mean square algorithm with application to adaptive sparse channel estimation," *EURASIP J. Wirel. Commun. Netw.*, vol. 2013, no. 1, p. 204, 2013. Article (CrossRef Link)

[13] G. Gui, W. Peng, and F. Adachi, "Sparse least mean fourth algorithm for adaptive channel estimation in low signal-to-noise ratio region," *Int. J. Commun. Syst.*, vol. 27, no. 11, pp. 3147–3157, 2014. Article (CrossRef Link)

[14] G. Gui, L. Xu, and S. Matsushita, "Improved adaptive sparse channel estimation using mixed square/fourth error criterion," *J. Franklin Inst.*, vol. 352, no. 10, pp. 4579–4594, 2015. Article (CrossRef Link)

[15] Y. Li, Y. Wang, and T. Jiang, "Sparse Channel Estimation Based on a p -Norm-Like Constrained Least Mean Fourth Algorithm," in *Proc. of 2015 International Conference on Wireless Communications & Signal Processing (WCSP) Nanjing, China* 15-17 Oct. 2015, 2015, pp. 1–4. Article (CrossRef Link)

[16] Y. Li and M. Hamamura, "Zero-attracting variable-step-size least mean square algorithms for adaptive sparse channel estimation," *Int. J. Adapt. Control Signal Process.*, no. 9, pp. 1–18, 2015. Article (CrossRef Link)

[17] C. Xiao, Y. R. Zheng, and N. C. Beaulieu, "Novel sum-of-sinusoids simulation models for rayleigh and rician fading channels," *IEEE Trans. Wirel. Commun.*, vol. 5, no. 12, pp. 3667–3678, 2006. Article (CrossRef Link)

[18] M. F. Pop and N. C. Beaulieu, "Limitations of sum-of-sinusoids fading channel simulators," *IEEE Trans. Commun.*, vol. 49, no. 4, pp. 699–708, 2001. Article (CrossRef Link)

[19] M. Agiwal, A. Roy, and N. Saxena, "Next generation 5G wireless networks: A comprehensive survey," *IEEE Commun. Surv. Tutorials*, vol. 18, no. 3, pp. 1617–1655, 2016. Article (CrossRef Link)

[20] A. Osseiran, F. Boccardi, V. Braun, K. Kusume, P. Marsch, M. Maternia, O. Queseth, M. Schellmann, H. Schotten, H. Taoka, H. Tullberg, M. a. Uusitalo, B. Timus, and M. Fallgren, "Scenarios for 5G mobile and wireless communications: The vision of the METIS project," *IEEE Commun. Mag.*, vol. 52, no. May, pp. 26–35, 2014. Article (CrossRef Link)

[21] Z. Ding, X. Lei, G. K. Karagiannidis, R. Schober, J. Yuan, and V. Bhargava, "A Survey on Non-Orthogonal Multiple Access for 5G Networks: Research Challenges and Future Trends," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 10, pp. 2181–2195, 2017. Article (CrossRef Link)

[22] S. Chen and J. Zhao, "The requirements, challenges, and technologies for 5G of terrestrial mobile telecommunication," *IEEE Commun. Mag.*, vol. 52, no. May, pp. 36–43, 2014.

[23] J. Zhang, "The interdisciplinary research of big data and wireless channel: A cluster-nuclei based channel model," *China Commun.*, vol. 13, no. 2, pp. 14–26, 2017. Article (CrossRef Link)

[24] L. Lu, G. Li, a. L. Swindlehurst, A. Ashikhmin, and R. Zhang, "An overview of massive MIMO: Benefits and challenges," *IEEE J. Sel. Top. Signal Process.*, vol. 8, no. 5, pp. 742–758, 2014. Article (CrossRef Link)

[25] M. Wu, B. Yin, G. Wang, C. Dick, J. Cavallaro, and C. Studer, "Large-Scale MIMO Detection for 3GPP LTE: Algorithm and FPGA Implementation," *IEEE J. Sel. Top. Signal Process.*, vol. PP, no. 99, pp. 1–1, 2014. Article (CrossRef Link)

[26] C. Turan, M. S. Salman, and A. Eleyan, "A new variable step-size block LMS algorithm for a non-stationary sparse systems," in *Proc. of Proceedings of 12th International Conference on Electronics Computer and Computation (ICECCO)*, 2015, pp. 1–4. Article (CrossRef Link)

[27] Y. Chen, Y. Gu, and A. O. Hero III, "Sparse LMS for system identification," in *Proc. of IEEE International Conference on Acoustics, Speech and Signal Processing,Taipei, Taiwan*, 19-24 April 2009, 2009, pp. 3125–3128.Article (CrossRef Link)

[28] G. Gui and F. Adachi, "Improved least mean square algorithm with application to adaptive sparse channel estimation," *Eurasip J. Wirel. Commun. Netw.*, vol. 2013, no. 1, 2013. doi:10.1186/1687-1499-2013-204. Article (CrossRef Link)

[29] G. Gui and F. Adachi, "Sparse least mean fourth filter with zero-attracting L1-norm constraint," in *Proc. of 9th International Conference on Information, Communications and Signal Processing (ICICS), Tainan, Taiwan*, December 10-13, 2013, 2013, pp. 1–5. Article (CrossRef Link)

[30] G. Gui and F. Adachi, "Sparse least mean fourth algorithm for adaptive channel estimation in low signal-to-noise ratio region," *Int. J. Commun. Syst.*, vol. 27, no. 11, 2014. Article (CrossRef Link)

[31] J. Liu and S. L. Grant, "Proportionate adaptive filtering for block-sparse system identification," *IEEE/ACM Trans. Speech Lang. Process.*, vol. 24, no. 4, pp. 623–630, 2016. Article (CrossRef Link)

[32] Y. Li, Y. Wang, and T. Jiang, "Norm-adaption penalized least mean square/fourth algorithm for sparse channel estimation," *Signal Processing*, vol. 128, pp. 243–251, 2016. Article (CrossRef Link)

[33] Y. Li, Z. Jin, Y. Wang, and R. Yang, "A robust sparse adaptive filtering algorithm with a correntropy induced metric constraint for broadband multi-path channel estimation," *Entropy*, vol. 18, no. 10, p. 380, 2016. Article (CrossRef Link)

[34] A. S. Parameter and F. Penalized, "A Soft Parameter Function Penalized Normalized Maximum Correntropy Criterion Algorithm for Sparse System Identification," *Entropy*, vol. 1, no. 45, pp. 1–16, 2017. Article (CrossRef Link)

[35] S. Lim, "Combined LMS/F algorithm," *Electroincs Lett.*, vol. 33, no. 6, pp. 467–468, 1997. Article (CrossRef Link)

[36] G. Gui, A. Mehbodniya, and F. Adachi, "Least mean square/fourth algorithm for adaptive sparse channel estimation," in *Proc. of IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), London, UK*, 8-11 Sept. 2013, 2013, pp. 296–300. Article (CrossRef Link)

Saadat Dehgan was born in Iran, in 1990. He received his B.S. degree from the University Industrial of Martyrs Hawizah in 2014 in electrical engineering. Since then he is pursuing the M.S. degree with the Department of Electrical Engineering, Urmia University. His research interests include stochastic and adaptive signal processing and adaptive filter design.

Changiz Ghobadi was born on 1 June, 1960 in Iran. He received the B.Sc. degree in Electrical and Electronic Engineering and M.Sc. degree in Electrical and Telecommunication Engineering from Isfahan University of Technology, Isfahan, Iran and Ph.D. degree in Electrical-Telecommunication from University of Bath, Bath, UK in 1998. From 1998 he was an Assistant Professor and now is full Professor in the Department of Electrical Engineering, of Urmia University, Urmia, Iran. His primary research interests are in antenna design, radar, and adaptive filters.

Javad Nourinia received his B.Sc. in Electrical and Electronic Engineering from Shiraz University and M.Sc. degree in Electrical and Telecommunication Engineering from Iran University of Science and Technology, and Ph.D. degree in Electrical and Telecommunication from University of Science and Technology, Tehran, Iran in 2000. From 2000 he was an assistant professor and now is full professor in the Department of Electrical Engineering, of Urmia University, Urmia, Iran. His primary research interests are in antenna design, numerical methods in electromagnetic, microwave circuits.

Jie Yang is a lecture in Nanjing University of Posts and Telecommunications, Nanjing, China. Her research interests are adaptive filter, compressive sensing, sparse dictionary designing, channel estimation, and advanced wireless techniques.

Guan Gui received the Dr. Eng degree in information and communication engineering from University of Electronic Science and Technology of China (UESTC), Chengdu, China, in 2011. From October 2009 to March 2012, with the financial supported from the China scholarship council (CSC) and the global center of education (ECOE) of Tohoku University, he joined the wireless signal processing and network laboratory (Prof. Adachi's laboratory), Department of Communications Engineering, Graduate School of Engineering, Tohoku University as for research assistant as well as postdoctoral research fellow,respectively. From September 2012 to March 2014, he was supported by Japan society for the promotion of science (JSPS) fellowship as postdoctoral research fellow at same laboratory. From April 2014 to October 2015, he was an Assistant Professor in Department of Electronics and Information System, Akita Prefectural University. Since November 2015, he has been a professor with Nanjing University of Posts and Telecommunications (NUPT), Nanjing, China. He is currently engaged in research of multidimensional system control, super-resolution radar imaging, adaptive filter, compressive sensing, sparse dictionary designing, channel estimation, and advanced wireless techniques. He is a member of Institute of Electrical and Electronics Engineers (IEEE).

Dr. Gui has been an Associate Editor for the Wiley Journal of Security and Communication Networks since 2012. He received IEEE International Conference on Communications (ICC) Best Paper Award in years 2014 and 2017, as well as IEEE Vehicular Technology Conference (VTC-spring) Best Student Paper Award in year 2014. He was also selected as for Jiangsu Distinguished Professor and Jiangsu High-level Innovation and Entrepreneurial Talent in year 2016 and "1311 Talent Plan"Nanjing University of Posts and Telecommunications in year 2017.

Ehsan Mostafapour was born in west Azerbaijan Province, Urmia, Iran, in 1988. He received the B.S. the M.S. degrees from the Islamic Azad University, in 2010 and 2012, respectively, both in telecommunication engineering. He is currently pursuing the Ph.D. degree with the Department of Electrical Engineering, Urmia University. His research interests include stochastic and adaptive signal processing, wireless communications, adaptive networks and neural networks.