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Research Article

Sparsity-constraint LMS Algorithms for Time-varying UWB Channel Estimation

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Abstract: Sparsity constraint channel estimation using compressive sensing approach has gained widespread interest in recent times. Mostly, the approach utilizes either the l_1-norm or l_0-norm relaxation to improve the performance of LMS-type algorithms. In this study, we present the adaptive channel estimation of time-varying ultra wideband channels, which have shown to be sparse, in an indoor environment using sparsity-constraint LMS and NLMS algorithms for different sparsity measures. For a less sparse CIR, higher weightings are allocated to the sparse penalty term. Simulation results show improved performance of the sparsity-constraint algorithms in terms of convergence speed and mean square error performance.

Keywords: Compressive sensing, (N) LMS algorithms, sparse channel estimation, time-varying channels, ultra wideband

INTRODUCTION

The popularity of Ultra Wideband (UWB) signaling in recent times is chiefly due to the very high-data transmission rates it can offer (Kaiser and Zheng, 2010; Kaiser *et al*., 2009). It has seen extensive use in applications requiring stationary transceivers. Other applications, such as vehicle-to-vehicle propagation (e.g., communication between mobile robots) or vehicle-to-infrastructure propagation (e.g., mobile robot to base station communication), that require very high-data transmission rates can also take advantage of UWB technology.

The need for accurate Channel State Information (CSI) at the receiver side of many wideband communication systems is of utmost importance and UWB systems are no exception. Instructively, most of these channels have shown to be sparse. In fact, the UWB channel is either “dense” or “sparse” depending on the measured bandwidth and the environment under consideration (Molisch, 2005). Adaptive Channel Estimation (ACE) is an effective approach for estimating such channels. There are many ACE algorithms, such as the Least Mean Square (LMS) and the Recursive Least Squares (RLS) algorithms (Diniz, 2013; Sayed, 2008; Haykin, 2002). However, these algorithms are not able to exploit the channel sparsity due to their lack of sparse characteristics.

In recent times, some ACE algorithms have exploited channel sparsity to improve the identification performance (Gui *et al*., 2013a; Das *et al*., 2011; Taheri and Vorobyov, 2014; Gui and Adachi, 2013; Gui *et al*., 2013b; Chen *et al*., 2009). These algorithms adopt the Compressive Sensing (CS) approach (Donoho, 2006). Many of these algorithms are shown to be robust in noisy environments. Chen *et al*. (2009), proposed the l_1-norm relaxation to improve the performance of the LMS algorithm, resulting in the Zero-Attracting LMS (ZA-LMS) and Reweighted ZA-LMS (RZA-LMS). Gui and Adachi (2013) also proposed algorithms utilizing the l_0-norm sparsity-constraint, which promises to a more accurate channel estimation.

To the best of our knowledge, ACE of UWB channels using sparsity-constraint algorithms is yet to be exploited. In this study, we present the ACE of time-varying UWB channels in an indoor environment using sparsity-constraint LMS and Normalized LMS (NLMS) algorithms for different sparsity measures. This work is unique in the sense that the Channel Impulse Response (CIR) used in the analysis is based on time-domain UWB channel measurements.

SYSTEM MODEL AND PROBLEM FORMULATION

Preliminaries: Considering the receiver side of a typical communication system, we can represent the system identification system like as shown in Fig. 1 to discuss channel estimation algorithms. Given that, $d(k)$ is the desired signal of an adaptive filter, then:

$$d(k) = \mathbf{x}^T(k)\mathbf{h} + n(k) \tag{1}$$

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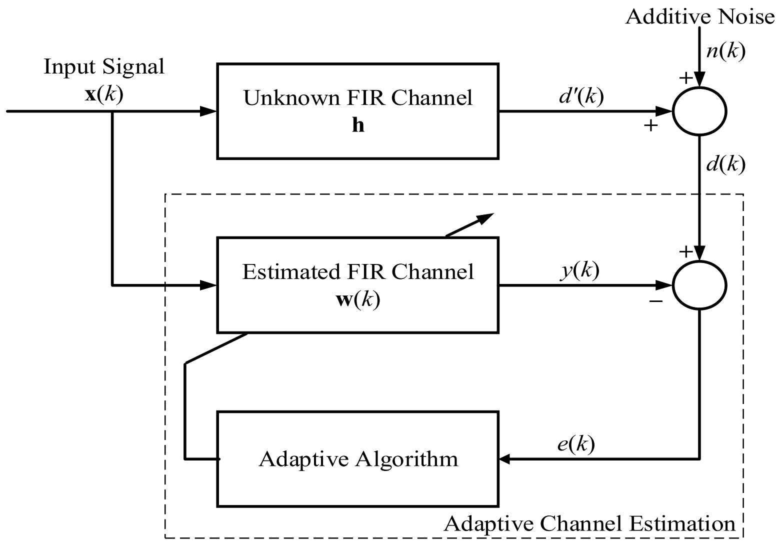

Fig. 1: A typical system identification block diagram

where, x $(k) = [x_0(k)\ x_1(k)\ \dots\ x_{N-1}(k)]^T$ is the input signal vector at iteration k for an N-length channel vector, $n(k)$ is the system noise signal, which is a zero-mean uncorrelated sequence that is independent of $x(k)$, h = $[h_0\ h_1\ \dots\ h_{N-1}]^T$ is the channel vector of the communication system that we wish to estimate, $y(k) = \mathrm{x}^T(k)\,\mathrm{w}(k)$, w $(k) = [w_0(k)\ w_1(k)\ \dots\ w_{N-1}(k)]^T$ is the filter weight coefficient vector and $[\bullet]^T$ denotes vector transpose. For simplicity, the filter is assumed to have the same structure as the unknown system. Thus, the a priori estimation error $e(k)$ is also given by:

$$e(k) = d(k) - \mathbf{x}^T(k)\mathbf{w}(k) \tag{2}$$

(N) LMS algorithm: The LMS algorithm is the most widely used adaptive system mainly due to its ease of implementation and robustness in the presence of numerical errors. Based on (2), the standard LMS cost function is given as:

$$\mathbf{J}\left[\mathbf{w}(k)\right] = \frac{1}{2}e^2(k) \tag{3}$$

Thus, the update equation of the LMS algorithm is described by the equation:

$$\mathbf{w}(k+1) = \mathbf{w}(k) - \mu\frac{\partial J(k)}{\partial \mathbf{w}(k)} = \mathbf{w}(k) + \mu e(k)\mathbf{x}(k) \tag{4}$$

where, μ is the step-size and it is chosen such that; $0<\mu\leq 1$.

Unfortunately, the LMS algorithm is sensitive to the scaling of its input. This makes it very hard (if not unfeasible) to choose a step-size that guarantees stability of the algorithm (Haykin, 2002). The NLMS algorithm solves this problem by normalizing the adaptive error update section with the input power. Thus, the NLMS algorithm is described by the equation:

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu\frac{\mathbf{x}(k)}{\gamma + \mathbf{x}^T(k)\mathbf{x}(k)}e(k) \tag{5}$$

where, γ is a regulation parameter, which is included in order to avoid large step sizes when $\mathrm{x}^T(k)\ \mathrm{x}(k)$ becomes small.

CS-BASED CHANNEL ESTIMATION ALGORITHMS

The LMS algorithm can simply be expressed as:

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \left[\textit{Adaptive Error Update}\right] \tag{6}$$

whereby the adaptive error update determines how fast the algorithm converges and its ability to exploit the sparsity inherent in UWB channels. The basic principle of CS-based sparse adaptive filtering is the introduction of an appropriate sparse penalty which can be generalized as follows (Gui and Adachi, 2013):

$$\begin{aligned}\mathbf{w}(k+1) &= \mathbf{w}(k) + \left[\textit{Adaptive Error Update}\right]\\ &+ \left[\textit{Sparse Penalty}\right]\end{aligned} \tag{7}$$

Thus from (7), various sparse penalties can be introduced to capitalize on the sparse structure and improve convergence. The conventional sparse penalties include the l_1-norm sparse constraints, which is added to the cost function of the LMS algorithm. This results in the LMS update with a zero-attractor, namely Zero-Attracting LMS (ZA-LMS) and Reweighted ZA-LMS (RZA-LMS) algorithms (Chen *et al*., 2009). The quest for further improvement on the estimation performance has also led to the l_p-norm LMS (LP-LMS) algorithm (Taheri and Vorobyov, 2011) and the l_0-norm LMS (L0-LMS) algorithm (Gui and Adachi, 2013). The associated NLMS versions of these CS-based algorithms have also been proposed by Gui and Adachi (2013).

LMS-based sparse channel estimation algorithms: This subsection presents the LMS adaptive sparse CE methods.

ZA-LMS algorithm: The cost function of the ZA-LMS algorithm is given as:

$$\mathbf{J}_{\mathrm{ZA}}\left[\mathbf{w}(k)\right]=\frac{1}{2}e^{2}(k)+\lambda_{\mathrm{ZA}}\left\|\mathbf{w}(k)\right\|_{1} \tag{8}$$

where, λ_{ZA} is the regularization parameter to balance the estimation error and sparse penalty of $\mathbf{w}$ (k) and $\|\boldsymbol{w}\ (k)\|_1$ is the l_0-norm sparse penalty function. The corresponding update equation of the ZA-LMS algorithm is:

$$\begin{aligned}\mathbf{w}(k+1)&=\mathbf{w}(k)-\mu\frac{\partial\mathbf{J}_{\mathrm{ZA}}(k)}{\partial\mathbf{w}(k)}\\&=\mathbf{w}(k)+\mu e(k)\mathbf{x}(k)-\kappa_{\mathrm{ZA}}\operatorname{sgn}\left[\mathbf{w}(k)\right]\end{aligned} \tag{9}$$

where, $\kappa_{\mathrm{ZA}}=\mu\lambda_{\mathrm{ZA}}$ and $\operatorname{sgn}(\cdot)$ is a component-wise function defined as:

$$\operatorname{sgn}(x)=\begin{cases}\frac{x}{|x|} & x\neq 0\\ 0 & \text{otherwise}\end{cases} \tag{10}$$

RZA-LMS algorithm: The cost function of the RZA-LMS algorithm is given as:

$$\mathbf{J}_{\mathrm{RZA}}\left[\mathbf{w}(k)\right]=\frac{1}{2}e^{2}(k)+\lambda_{\mathrm{RZA}}\sum_{i=1}^{N}\log\left(1+\varepsilon_{\mathrm{RZA}}\left|w_i(k)\right|\right) \tag{11}$$

where, $\lambda_{RZA} > 0$ is the regularization parameter and ε_{RZA} is a positive threshold. The update equation in vector form can be expressed as:

$$\begin{aligned}\mathbf{w}(k+1)&=\mathbf{w}(k)-\mu\frac{\partial\mathbf{J}_{\mathrm{RZA}}(k)}{\partial\mathbf{w}(k)}\\&=\mathbf{w}(k)+\mu e(k)\mathbf{x}(k)-\kappa_{\mathrm{RZA}}\frac{\operatorname{sgn}\left[\mathbf{w}(k)\right]}{1+\varepsilon_{\mathrm{RZA}}\left|\mathbf{w}(k)\right|}\end{aligned} \tag{12}$$

where $\kappa_{\mathrm{RZA}}=\mu\lambda_{\mathrm{RZA}}\varepsilon_{\mathrm{RZA}}$.

L0-LMS algorithm: Consider l_0-norm penalty on the LMS cost function which forces $\mathbf{w}$ (k) to approach zero. The cost function is given by:

$$\mathbf{J}_{\mathrm{L0}}\left[\mathbf{w}(k)\right]=\frac{1}{2}e^{2}(k)+\lambda_{\mathrm{L0}}\left\|\mathbf{w}(k)\right\|_{0} \tag{13}$$

where, $\lambda_{L0} > 0$ is a regulation parameter for balancing the penalty and estimation error and $\|\boldsymbol{w}\ (k)\|_0$ is the l_0-norm sparse penalty function. Since the l_0-norm is a Non-Polynomial (NP) hard problem (Gu *et al*., 2009), in order to reduce the computational complexity, we replace it with an approximate continuous function:

$$\left\|\mathbf{w}(k)\right\|_{0}\approx\sum_{i=0}^{N-1}\left(1-e^{-\beta\left|w_i(k)\right|}\right) \tag{14}$$

Therefore, the cost function in (13) can be rewritten as:

$$\mathbf{J}_{\mathrm{L0}}\left[\mathbf{w}(k)\right]=\frac{1}{2}e^{2}(k)+\lambda_{\mathrm{L0}}\sum_{i=0}^{N-1}\left(1-e^{-\beta\left|w_i(k)\right|}\right) \tag{15}$$

From the first order Taylor series expansion of the exponential function:

$$e^{-\beta\left|w_i(k)\right|}\approx\begin{cases}1-\beta\left|w_i(k)\right| & \text{when } \left|w_i(k)\right|\leq\frac{1}{\beta}\\ 0 & \text{otherwise}\end{cases} \tag{16}$$

The update equation of the l_0-norm LMS is given as:

$$\mathbf{w}(k+1)=\mathbf{w}(k)+\mu e(k)\mathbf{x}(k)-\kappa_{\mathrm{L0}}\beta\operatorname{sgn}\left(\mathbf{w}(k)\right)e^{-\beta\mathbf{w}(k)} \tag{17}$$

where, $\kappa_{\mathrm{L0}}=\mu\lambda_{\mathrm{L0}}$. Unfortunately, the exponential function in (17) will also cause high computational complexity. To further reduce the complexity, an approximation function F $[\boldsymbol{w}$ $(k)]$ is introduced. Thus the l_0-norm LMS sparse ACE is given as:

$$\mathbf{w}(k+1)=\mathbf{w}(k)+\mu e(k)\mathbf{x}(k)-\kappa_{\mathrm{L0}}F\left[\mathbf{w}(k)\right] \tag{18}$$

with F $[\boldsymbol{w}$ $(k)]$ defined as:

$$F\left[\mathbf{w}(k)\right]=\begin{cases}2\beta^{2}\mathbf{w}(k)-2\beta\operatorname{sgn}\left(\mathbf{w}(k)\right) & \text{when } \mathbf{w}(k)\leq\frac{1}{\beta}\\ 0 & \text{otherwise}\end{cases} \tag{19}$$

For all i ϵ {1, 2, …, N}

NLMS-based sparse channel estimation algorithms: The NLMS-based adaptive sparse CE algorithms possess the ability to mitigate the scaling interference of the training signal. This effect is due to the fact that NLMS-based methods estimate the sparse channel by normalizing the power of the training signal **x** (k). This subsection presents the NLMS adaptive sparse CE methods.

ZA-NLMS algorithm: From (9), the update equation of the ZA-NLMS algorithm is given as:

$$\mathbf{w}(k+1)=\mathbf{w}(k)+\mu\frac{\mathbf{x}(k)}{\gamma+\mathbf{x}^T(k)\mathbf{x}(k)}e(k)-\kappa_{\mathrm{ZAN}}\,\mathrm{sgn}\left[\mathbf{w}(k)\right] \quad (20)$$

where, $\kappa_{\mathrm{ZAN}}=\mu\lambda_{\mathrm{ZAN}}$ and λ_{ZAN} are regulation parameters of the ZA-NLMS algorithm.

RZA-NLMS algorithm: From (12), the update equation of the RZA-NLMS algorithm is given as:

$$\mathbf{w}(k+1)=\mathbf{w}(k)+\mu\frac{\mathbf{x}(k)}{\gamma+\mathbf{x}^T(k)\mathbf{x}(k)}e(k)-\kappa_{\mathrm{RZAN}}\frac{\mathrm{sgn}\left[\mathbf{w}(k)\right]}{1+\varepsilon_{\mathrm{RZAN}}\left|\mathbf{w}(k)\right|} \quad (21)$$

where, $\kappa_{\mathrm{RZAN}}=\mu\lambda_{\mathrm{RZAN}}\varepsilon_{\mathrm{RZAN}}$ and λ_{RZAN} are regulation parameters of the RZA-NLMS algorithm.

L0-NLMS algorithm: From (18), the update equation of the L0-NLMS algorithm is given as:

$$\mathbf{w}(k+1)=\mathbf{w}(k)+\mu\frac{\mathbf{x}(k)}{\gamma+\mathbf{x}^T(k)\mathbf{x}(k)}e(k)-\kappa_{\mathrm{L0N}}F\left[\mathbf{w}(k)\right] \quad (22)$$

where $\kappa_{\mathrm{L0N}}=\mu\lambda_{\mathrm{L0N}}$ and λ_{L0N} are regulation parameters of the L0-NLMS algorithm. The approximation function F [**w** (k)] is as defined in (19).

RESULTS AND DISCUSSION

The analysis carried out in this study uses wireless Channel Impulse Response (CIR) measurements conducted by means of Time Domain's PulsON® 410 Ranging and Communications Module (P410 RCM). It is an UWB radio transceiver, which with accompanying Channel Analysis Tool (CAT) provides impulse responses of an UWB channel. The setup used for collecting the Radio Frequency (RF) data is as shown in Fig. 2.

The transceiver transmits in a frequency range of 3.1-5.3 GHz and at a center frequency of 4.3 GHz. The measurements were conducted in an indoor environment. During the measurement, the receiver, which was connected to the data collecting computer, was held stationary as the transmitter was moved at a velocity of 1 m/sec. The transmit gain was set to 44 dB with a data packet size of 32 bit. A step size of 32 was used which allows one measurement every 61 ps. Figure 3 is a CIR for one of the measurements, which is sparse in nature. The channel length of the CIR, obtained from the measurement, is 1632.

Fig. 2: Setup for collecting RF propagating data during the measurements

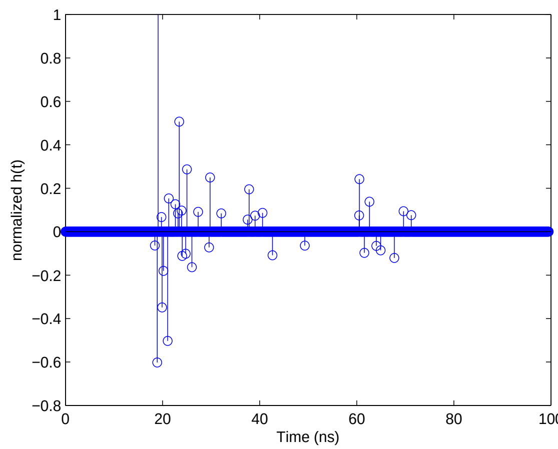

Fig. 3: Channel impulse response (scan #10, thresh = 25 dB)

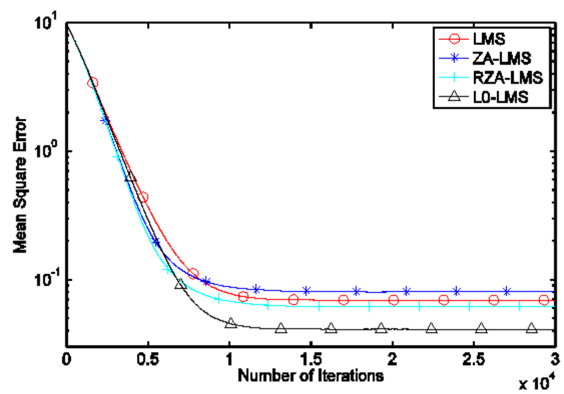

Fig. 4: MSE performance comparison for LMS-based algorithms when the measured CIR is dense at SNR of 10 dB

Khong and Naylor (2006) defines sparseness measure of a CIR as:

$$\xi(k)=\frac{N}{N-\sqrt{N}}\left[1-\frac{\left\|\mathbf{w}(k)\right\|_1}{\sqrt{N}\left\|\mathbf{w}(k)\right\|_2}\right] \quad (23)$$

where, N is the length of the channel vector **w** (k). Note that for any given CIR, $0\le\xi(k)\le1$, where $\xi(k)=1$ and

ξ (k) = 0 refers to highly sparse and least sparse respectively. From our measurement results, the minimum and maximum sparseness measure values were found to be 0.756 and 0.94606, respectively.

We conducted several simulations for the analysis. Each simulation result is the steady-state statistical average of 200 runs, with 30000 iterations in each run. The received Signal-to-Noise Ratio (SNR) is defined as $10\log\left(E_0/\sigma_n^2\right)$, where E_0 = 1 is the received signal power and the noise power is given by $\sigma_n^2 = 10^{-\mathrm{SNR}/10}$. We compared the performance of the algorithms for three separate SNR values: 10, 20 and 30 dB, respectively.

The channel estimators are evaluated by averaging the Mean Square Error (MSE) which is defined as (Li and Hamamura, 2014):

$$\mathrm{MSE}\left[\mathbf{w}(k)\right] = \mathrm{E}\left[\left\|\mathbf{w} - \hat{\mathbf{w}}(k)\right\|_2^2\right] \quad (24)$$

where, $\mathbf{w}$ and $\hat{\mathbf{w}}$ (k) are the actual and the k^{th} iterative channel update, respectively and $\|\cdot\|_2$ is the Euclidean norm operator.

In the first experiment, we assess the estimation performance of the LMS-based algorithms. The performance comparison of the LMS, ZA-LMS, RZA-LMS and L0-LMS algorithms when the measured CIR is dense is shown in Fig. 4 to 6 and that of when the measured CIR is sparse is also shown in Fig. 7 to 9. A step-size of 0.0005 was used for this experiment. Other parameter values used for the experiment are given in Table 1. A cursory look at Fig. 4 to 9 shows that the sparse algorithms performs better in the sparse channels. Additionally, in both cases, performance improves considerably with increasing SNR values but with deteriorating convergence performance. In the dense CIR scenario, shown in Fig. 4 to 7, L0-LMS provides the best performance in all three SNR regimes with the best convergence when SNR is either 10 or 20 dB. Ironically, LMS performs better than ZA-LMS when SNR is 10 dB but with poor convergence.

In the second experiment, we evaluate the estimation performance of the NLMS-based algorithms.

Table 1: Simulation parameters of the (N) LMS algorithms at different SNR values

	Simulation parameters for different SNR values		
Experiment	SNR = 10 dB	SNR = 20 dB	SNR = 30 dB
LMS simulation parameters when CIR is dense (ξ (k) = 0.756)	$\mu = 5\times10^{-4}$ $\kappa_{ZA} = \kappa_{RZA} = \kappa_{L0} = 1\times10^{-5}$ $\varepsilon_{RZA} = 1$ $\beta = 0.09$	$\mu = 5\times10^{-4}$ $\kappa_{ZA} = \kappa_{RZA} = \kappa_{L0} = 1\times10^{-6}$ $\varepsilon_{RZA} = 1$ $\beta = 0.9$	$\mu = 5\times10^{-4}$ $\kappa_{ZA} = \kappa_{RZA} = \kappa_{L0} = 1\times10^{-6}$ $\varepsilon_{RZA} = 1$ $\beta = 0.1$
LMS simulation parameters when CIR is sparse (ξ (k) = 0.94606)	$\mu = 5\times10^{-4}$ $\kappa_{ZA} = \kappa_{RZA} = \kappa_{L0} = 5\times10^{-6}$ $\varepsilon_{RZA} = 1$ $\beta = 0.9$	$\mu = 5\times10^{-4}$ $\kappa_{ZA} = \kappa_{RZA} = \kappa_{L0} = 5\times10^{-6}$ $\varepsilon_{RZA} = 1$ $\beta = 0.5$	$\mu = 5\times10^{-4}$ $\kappa_{ZA} = \kappa_{RZA} = \kappa_{L0} = 1\times10^{-6}$ $\varepsilon_{RZA} = 1$ $\beta = 0.5$
NLMS simulation parameters when CIR is dense (ξ (k) = 0.756)	$\mu = 0.8$ $\gamma = 1\times10^{-5}$ $\kappa_{ZAN} = \kappa_{RZAN} = \kappa_{L0N} = 1\times10^{-5}$ $\varepsilon_{RZAN} = 1$ $\beta = 0.05$	$\mu = 0.8$ $\gamma = 1\times10^{-5}$ $\kappa_{ZAN} = \kappa_{RZAN} = \kappa_{L0N} = 9\times10^{-7}$ $\varepsilon_{RZAN} = 1$ $\beta = 0.99$	$\mu = 0.8$ $\gamma = 1\times10^{-5}$ $\kappa_{ZAN} = \kappa_{RZAN} = \kappa_{L0N} = 9\times10^{-7}$ $\varepsilon_{RZAN} = 1$ $\beta = 0.9$
NLMS simulation parameters when CIR is sparse (ξ (k) = 0.94606)	$\mu = 0.8$ $\gamma = 1\times10^{-5}$ $\kappa_{ZAN} = \kappa_{RZAN} = \kappa_{L0N} = 9\times10^{-7}$ $\varepsilon_{RZAN} = 1$ $\beta = 0.9$	$\mu = 0.8$ $\gamma = 1\times10^{-5}$ $\kappa_{ZAN} = \kappa_{RZAN} = \kappa_{L0N} = 9\times10^{-7}$ $\varepsilon_{RZAN} = 1$ $\beta = 0.9$	$\mu = 0.8$ $\gamma = 1\times10^{-5}$ $\kappa_{ZAN} = \kappa_{RZAN} = \kappa_{L0N} = 9\times10^{-7}$ $\varepsilon_{RZAN} = 1$ $\beta = 0.99$

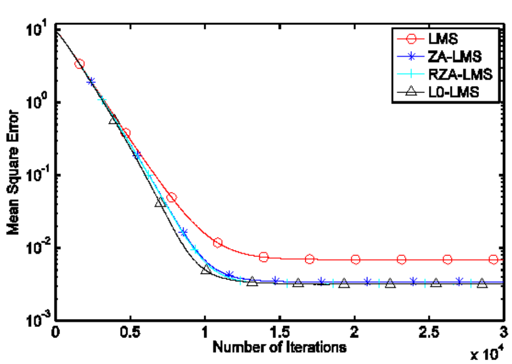

Fig. 5: MSE performance comparison for LMS-based algorithms when the measured CIR is dense at SNR of 20 dB

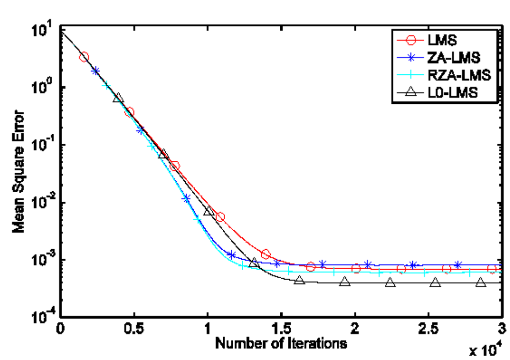

Fig. 6: MSE performance comparison for LMS-based algorithms when the measured CIR is dense at SNR of 30 dB

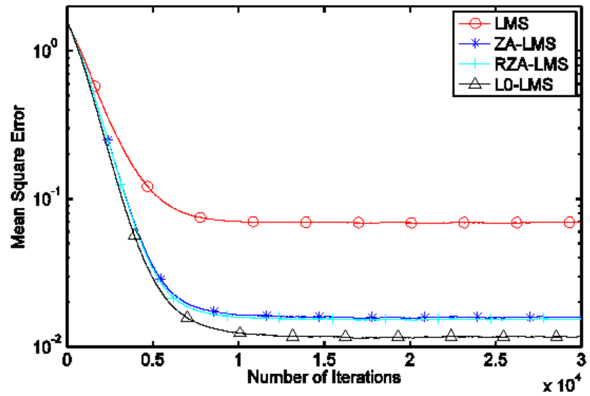

Fig. 7: MSE performance comparison for LMS-based algorithms when the measured CIR is sparse at SNR of 10 dB

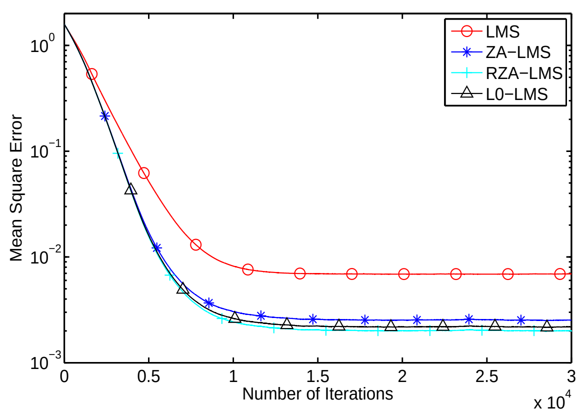

Fig. 8: MSE performance comparison for LMS-based algorithms when the measured CIR is sparse at SNR of 20 dB

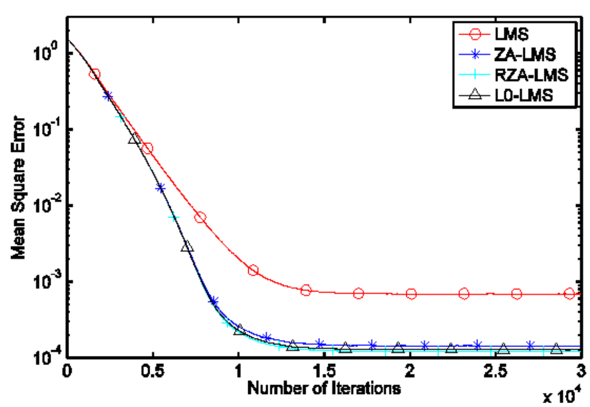

Fig. 9: MSE performance comparison for LMS-based algorithms when the measured CIR is sparse at SNR of 30 dB

The performance comparison of the NLMS, ZA-NLMS, RZA-NLMS and L0-NLMS algorithms when the measured CIR is dense is shown in Fig. 10 to 12 and that of when the measured CIR is sparse is also

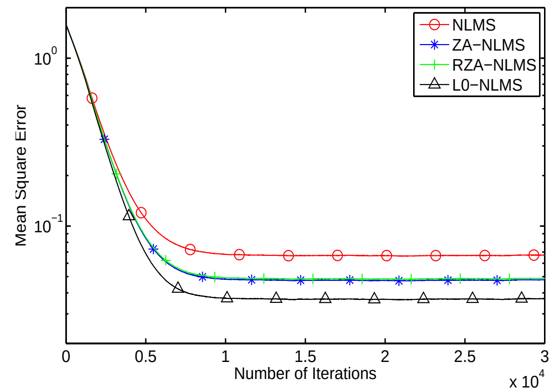

Fig. 10: MSE performance comparison for NLMS-based algorithms when the measured CIR is dense at SNR of 10 dB

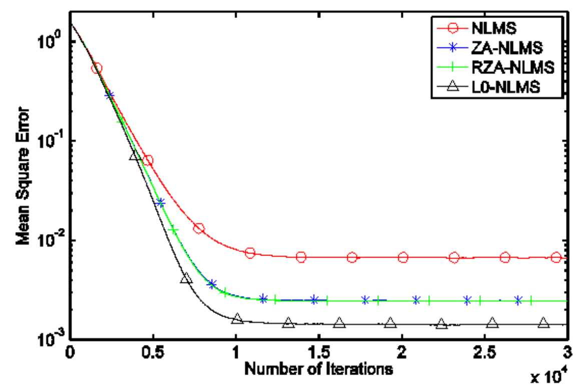

Fig. 11: MSE performance comparison for NLMS-based algorithms when the measured CIR is dense at SNR of 20 dB

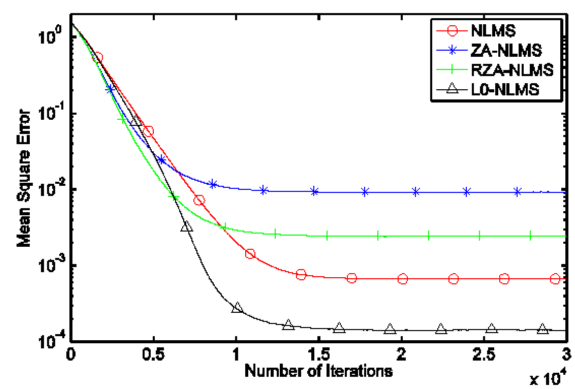

Fig. 12: MSE performance comparison for NLMS-based algorithms when the measured CIR is dense at SNR of 30 dB

shown in Fig. 13 to 15. In this experiment, we used a step-size of 0.8. Other parameter values used for the experiment are also present in Table 1. In this experiment, similar to the LMS experiment, performance improves as SNR values increase but with deteriorating convergence performance. Figure 10 to

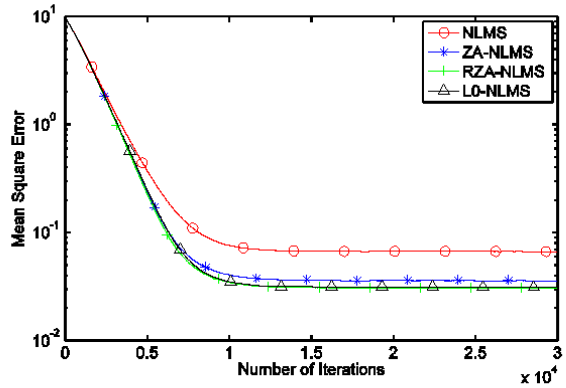

Fig. 13: MSE performance comparison for NLMS-based algorithms when the measured CIR is sparse at SNR of 10 dB

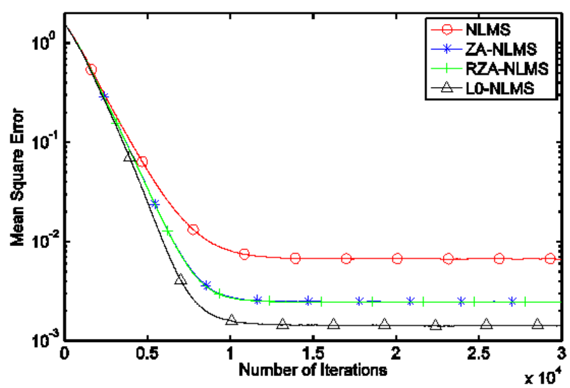

Fig. 14: MSE performance comparison for NLMS-based algorithms when the measured CIR is sparse at SNR of 20 dB

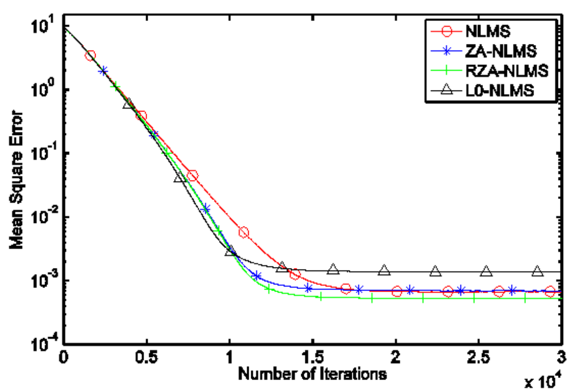

Fig. 15: MSE performance comparison for NLMS-based algorithms when the measured CIR is sparse at SNR of 30 dB

12, L0-NLMS performance is best for SNR of 10 dB (Fig. 10) and 20 dB (Fig. 11), but worst for 30 dB (Fig. 12) even though it has the best convergence. In addition, the RZA-NLMS performs best for dense CIR when SNR is 30 dB. Similarly, in Fig. 13 to 15, L0-NLMS performs best in all three scenarios. It is worth noting that the NLMS algorithm performed better than ZA-NLMS and RZA-NLMS in the sparse CIR and in the dense CIR case, better than L0-NLMS and same as ZA-NLMS when the SNR is 30 dB but with bad convergence behavior.

For the dense CIR, L0-NLMS performance remained almost constant when SNR is 20 dB (Fig. 11) or 30 dB (Fig. 12). In comparison to the sparse CIR, the MSE performance is about -30 dB when SNR is 20 dB (Fig. 14). Therefore, for the time-varying UWB channel, using L0-NLMS with an SNR of 20 dB will be the best option.

CONCLUSION

In this study, we presented the adaptive channel estimation of time-varying UWB channels in an indoor environment using sparsity-constraint LMS and Normalized LMS (NLMS) algorithms for different sparsity measures. Computer simulations show that for the time-varying UWB channel, using L0-NLMS with an SNR of 20 dB will be the best option. As future work, we will exploit the method of partial updating channel coefficients to help reduce the computational complexity of these algorithms.

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