A comparative study of blind and nonblind trainings in a single-carrier WiMAX (IEEE 802.16-2004) radio

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Abstract

Experimental and theoretical bit error rate performance evaluations of blind and nonblind training techniques are obtained by using a single-carrier WiMAX (IEEE 802.16-2004) radio for high-order quadrature amplitude modulation channels. Instead of using a certain type of channel profile, this study concentrates on true frequency-selective Rayleigh fading channels and also evaluates the fast fading scenario of Rayleigh channels in a real-time WiMAX radio environment around 3.5 GHz. The popular least mean squares (LMS) learning algorithm and constant modulus learning algorithm (CMA) are used as benchmarks in an investigation of nonblind and blind trainings, namely recursive least squares (RLS), modified-CMA, normalized-CMA, and fuzzy-CMA. The simulation results demonstrate that the theoretical and experimental studies are compatible with each other and extremely satisfying.

Key Words: *Experimental bit error rate, adaptive blind training, equalization, WiMAX (IEEE 802.16-2004), single carrier, constant modulus algorithm, quadrature amplitude modulation*

1. Introduction

The IEEE 802.16 working group was set up in 1999 to develop a new standard for broadband wireless access (BWA) and it published the first IEEE 802.16 standard in October 2001. In the first phase of the standard, single-carrier (SC) transmissions for 11-66 GHz frequency regions and multi-carrier (MC) transmissions for sub-11 GHz frequency regions were considered for fixed wireless access. With the publication of IEEE 802.16-2004 [1], these applications were extended to SC transmissions for sub-11 GHz systems. The 802.16e standard was also ratified in December 2005 allowing the upgrade from fixed BWA systems to mobile service provision up to vehicular speeds for sub-11 GHz systems [2].

The rapidly increasing usage of communication services leads to a continuous demand for faster and more robust data transmission systems and also for more efficient bandwidth usage. The major impairments affecting mobile communication systems are additive white Gaussian noise (AWGN) and intersymbol interference (ISI) where multipath fading causes considerable destruction in the amplitude and phase of the received signal.

Additionally, since the obstacles (moving objects, people etc.) are changing between the receiver and the transmitter, the channel established between these 2 units continuously varies. One of the best ways to mitigate these effects is to use blind or nonblind equalization/training techniques.

However, channel equalizer filter techniques have challenging convergence problems and implementation difficulties. In the telecommunications industry, equalizers are considered to be an extra cost for the system; thus, the simplest method in terms of implementation and training is chosen, without paying considerable attention to its performance. Simplicity is also very important for high-speed data communication systems; therefore, complex algorithms such as recursive least squares (RLS) or maximum likelihood sequence estimation (MLSE) algorithms are generally considered inappropriate even for high-performance equalizations. The most important part of the least mean squares (LMS) algorithm and the constant modulus algorithm (CMA) are their simplicity, as well as their stability and reliability; therefore, they have been used in several applications and implemented in many different units, such as in a digital signal processing algorithm [3] or in a field-programmable gate array device [4]. However, the training performance and speed of the LMS and CMA algorithms are quite poor in the case of equalization, since they solve an inverse convolution problem that may well extend to infinity. It is therefore necessary to improve the speed and accuracy of the LMS and CMA algorithms for high-performance applications.

The convergence rate of the LMS and CMA training algorithms is quite sensitive to the step-size parameter, which can be adjusted by monitoring the error value and other system parameters, of the update equation for an accurate and robust training. Using a large step size will cause a fast initial convergence but will result in larger fluctuation in the steady state; the results are opposite when a small step size is used. There are many successful works in the literature on controlling the step-size parameter of LMS and CMA algorithms to obtain better convergence and error performance using analytical or fuzzy logic-based approaches [5-11]. The variable step-size methods are also applied to CMA using analytical and recursive optimization techniques, as in the work by Du et al. [12]. However, this work, inspired by [5-11], aimed to design a training trajectory for the simple CMA using a fuzzy logic controller (FLC) loop, which provides a simple and more deterministic control on the training trajectory. Therefore, this study concentrated on fuzzy knowledge-based rules, and the rules were set up to learn the training behavior of the CMA and then adjust the step size due to current conditions such as the error level and trend of the mean square error. After obtaining stable training, the algorithm searches for the best decision by either increasing the step size to increase the convergence rate or decreasing the step size to execute fine tuning due to error constraints. The step size in the fuzzy logic-based LMS (F-LMS) [13] and fuzzy-CMA (F-CMA) [14] algorithms is modified by means of a sequence of operation that is adaptable via an instantaneous error value [15].

Thus far, blind equalizations have not been considered for commercial and high performance applications. Because the use of higher level of modulations, such as 16-QAM and 64-QAM, is possible in the WiMAX standard, this study investigates analyses of 16-QAM and 64-QAM modulations. For comparison, this study evaluates the bit error rate (BER) performance analyses of blind and nonblind equalizations in a real-time WiMAX radio experimental system, as well as in simulations of the system for frequency-selective Rayleigh fading channels. The obtained comparative BER performances for the blind and nonblind equalizations were quite comprehensive for indoor SC WiMAX radio applications.

The rest of the paper is organized as follows: Section 2 introduces the CMA-based adaptive blind equalizer trainings, which are, to the author's knowledge, the best blind training techniques. Section 3 explains the experimental system and measurement conditions. Section 4 presents the obtained BER performances to verify

the feasibility and robustness of the algorithms and finally, the paper is concluded in Section 5

2. Blind channel equalization

The baseband model of a digital communication channel can be characterized by a symbol-spaced finite impulse response (FIR) filter and an AWGN source. The received signal at the output of wideband channel v_k is given by:

$$v_k = \sum_{i=0}^{M} h_i x_{k-i} + \eta_k, \tag{1}$$

where x_k is the transmit data sequence, assumed to be independent and identically distributed (iid); h_i is the ith tap coefficient of the tapped-delay-line filter model of a channel; $M+1$ is the tap number of the channel; η_k is the iid AWGN component with zero mean and variance $\sigma_{\eta_k}^2$; and k is the time index. It should be mentioned here that, in this study, no offset frequency was considered and the samples are symbol spaced.

One of the best ways to mitigate ISI in Eq. (1) is to use an equalizer filter, which cancels the ISI while combining the multipath energy. In practice, a linear transversal equalizer (LTE) or a soft-decision data-directed decision feedback equalizer (DFE) is used for blind and nonblind equalizations. A LTE was used in this study; it has output $\hat{x}_k$, calculated by:

$$\hat{x}_k = \sum_{i=0}^{N} c_i v_{k-i}, \tag{2}$$

where $N+1$ is the tap number of the LTE and the c_i values are the LTE coefficients. For an ordinary training case, the error function of an equalizer is calculated by $\varepsilon_k = x_{k-Loffset} - \hat{x}_k$, where a training sequence, known by both the transmitter and receiver, is available, and where the number indicated by L_{offset} is attained for the adjustment of the center tap of the equalizer filter. However, if a training sequence is not issued in the transmission, one of the blind algorithms has to be applied to recover the transmitted data. For the adaptive blind training, the CMA is one of the best blind training techniques that use the following cost function:

$$\bar{J}_{CMA}(C) = E\{(|\hat{x}_k|^2 - \Delta_2)^2\}, \tag{3}$$

where C is the equalizer coefficient vector and $C = [c_0,\ c_1,\ ...,c_N]^T$ (where $[.]^T$ indicates the transpose of the matrix $[.]$), $\hat{x}_k$ is the kth estimate of the equalizer filter given by Eq. (2), $E\{\}$ is the expectation operator, and Δ_2 is a real positive constant calculated by $\Delta_2 = E\{|x_k|^4\}/E\{|x_k|^2\}$ using the transmit data.

The error function to verify the CMA criterion is:

$$\hat{\varepsilon}_k = \hat{x}_k(\Delta_2 - |\hat{x}_k|^2), \tag{4}$$

and, similar to the stochastic gradient algorithm, the adaptation of C as according to [16] is given by:

$$c_i = c_i + \mu\hat{\varepsilon}_k v_{k-i}^*, \quad i = 0,\ 1,\ ...N, \tag{5}$$

where μ is the step-size parameter of CMA, $\hat{\varepsilon}_k$ is the kth estimate of the error function using the CMA criterion, and v_{k-i}^* is the complex conjugate of v_{k-i}.

While the CMA is the best known of the blind equalizer training algorithms, its improved versions, modified CMA (M-CMA) and normalized CMA (N-CMA), have been found to be quite effective in blind training. The author also developed a novel CMA using fuzzy logic, F-CMA, as described in [14,15]. The modified CMA adjusts the step size by using a time-varying step-size parameter depending upon the squared Euclidean norm of the channel output vector and on the equalizer output [17]. The normalized CMA controls the step size for an efficient implementation by using the signal vector energy of the channel output, $\|v_k\|^2$, which is computed recursively, as in the normalized LMS algorithm [18]. The F-CMA has a similar update equation as in conventional CMA. However, the step-size parameter of F-CMA is adjusted according to the magnitude of error (MOE) and trend of error (TOE) using a fuzzy outer loop controller. Although the detailed form of F-CMA is available in [14,15], a brief description and implementation of the technique is given in the following paragraphs.
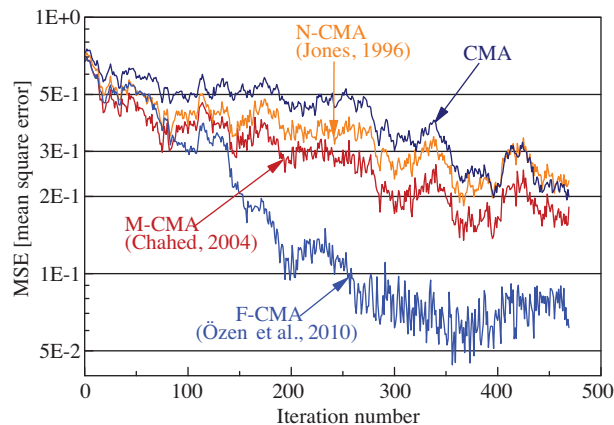

Figure 1. MSE performances of blind adaptive training (CMA) algorithms.

One of the important aspects of fuzzy logic is the implementation of a control system using experience-based rules defined in linguistic terms such as big, medium, small, or very small. Fuzzy logic enables the use of linguistic control definitions in the rule decision table (RDT), which is the main control unit developed by an expert or obtained by applying the fuzzy learning process. The required RDT for controlling the step-size parameters of CMA, following common rules, is revisited here.

Figure 1 shows the obtained mean square error (MSE) performances of adaptive blind training methods in simulations. The simulation conditions were similar to the systems in BER performance analysis, as explained in Section 4. The obtained MSE performances were published in [14], where the training features of blind training algorithms were extensively studied in order to find the best MSE curves, which were obtained by the values given in Table 2.

For nonblind equalizer training using the conventional least mean squares, a bigger step size is desirable to start a faster convergence, and a smaller step size is used to complete the training, as in the fine-tuning mode [13,15]. However, the convergence features of blind training are different, since an initial recovery of the equalizer filter is hardly obtained. A noticeable convergence in blind training is obtained after a certain delay, which is generally more than 100-200 training iterations, as shown in Figure 1. Therefore, in order to obtain a better recovery, the step size for blind training should start with a very small value, and then the step size of CMA should be increased to accelerate the convergence, provided that the error level is not increasing. Finally, if the error level is smaller and stable, then the step size should be decreased for better tuning for the coefficients.

These common rules of training can be applied to create a primary RDT. It is obvious that these rules can also be implemented by using conventional control techniques. However, fuzzy logic maintains the general control constraints at the very beginning, and its smooth transition between rules makes the system appropriate for development of an accurate control strategy.

The rules defined above can be summarized as follows.

If $MOE(k)$ is small and $TOE(k)$ is negative, then $\mu_{FCMA}(k)$ is small.

If $MOE(k)$ is small and $TOE(k)$ is zero, then $\mu_{FCMA}(k)$ is medium.

If $MOE(k)$ is small and $TOE(k)$ is positive, then $\mu_{FCMA}(k)$ is small.

If $MOE(k)$ is medium and $TOE(k)$ is negative, then $\mu_{FCMA}(k)$ is medium.

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$\cdots \qquad \cdots \qquad \cdots \qquad \cdots \qquad \cdots$

If $MOE(k)$ is high and $TOE(k)$ is negative, then $\mu_{FCMA}(k)$ is high.

MOE is calculated by:

$$MOE(k) = \frac{1}{M} \sum_{m=0}^{M-1} |\hat{\varepsilon}_k(k-m)|, \tag{6}$$

and TOE is calculated by:

$$TOE(k) = MOE(k) - MOE(k-1), \tag{7}$$

where the number of averaged error values, M, is used to obtain a short-term average of error in order to reduce the effect of instant noise over the control. Thus, a RDT with the explained rules above would be as in Table 1.

Table 1. A 3×3 rule decision table as an example.

MOE/TOE	Negative (N)	Zero (Z)	Positive (P)
Small (S)	$\mu_{FCMA}(S,N) =$ small	$\mu_{FCMA}(S,Z) =$ medium	$\mu_{FCMA}(S,P) =$ small
Medium (M)	$\mu_{FCMA}(M,N) =$ medium	$\mu_{FCMA}(M,Z) =$ small	$\mu_{FCMA}(M,P) =$ medium
High (H)	$\mu_{FCMA}(H,N) =$ medium	$\mu_{FCMA}(H,Z) =$ small	$\mu_{FCMA}(H,P) =$ high

At the beginning of the training, the magnitude of error (MOE) is high and the trend of error (TOE) is small or equal to zero; the step size should then be small, such that for (H_{MOE}, Z_{TOE}), the RDT would have an output equal to "small" ($\mu_{FCMA}(H,Z) =$ small). Second, if the error is high but decreasing, then the step size can be increased, such that for (H_{MOE}, N_{TOE}), the RDT would have a medium output ($\mu_{FCMA}(H,N) =$ medium). Third, if the error value is low and not changing, then the algorithm should penetrate the training algorithm due to changes in the error by increasing the step-size parameters, such that for (S_{MOE}, Z_{TOE}) the RDT would have a medium output ($\mu_{FCMA}(S,Z) =$ medium). These linguistic decisions, using an expert interpretation, can be carried out to fill the RDT.

3. The experimental system

The baseband signal preparation was done on a PC and uploaded to a vector signal generator, E4438C by Agilent (0-6 GHz), in the experimental WiMAX radio. In transmission, a raised-cosine filter with a cut-off rate of 0.35 was employed for the baseband filtering. A linear power amplifier (HMC409LP4 by Hittite Microwave) with 22 dBm and 35 dBm of IP1 and IP3 powers, respectively, was used before sending the signal to the antenna. During the experimental tests, 2 types of antennas were used: a biquad directional antenna with approximately

9 dBi of gain and a 60° aperture angle, and a bidirectional dipole antenna with a gain of less than 1 dBi (as measured during experiments).

A program written in C code on a PC at the transmitter side prepares a long experimental data sequence, as given in Figure 2. The prepared sequence contains a set of 255 symbols of a quadrature phase-shift keying (QPSK)-modulated pseudorandom noise (PN) sequence followed by 2 subsequences, each representing a burst set format, 16-QAM and 64-QAM, of the standard [1]. A CAZAC sequence with the length of 64 symbols, described on page 379 of [1], was used as unique words and repeated 3 times to create a burst set preamble at the beginning of each subsequence. The burst, as seen in Figure 2, was stored in the signal generator and transmitted repeatedly with a symbol rate of 20.48 Msample/s. The use of a combined data packet, as in Figure 2, provided for the comparative analysis of the modulation types.

The data packet has a complex PN sequence to detect the beginning of the data packet, since there is no feedback link in the experimental test bench to obtain the starting time of transmission. For nonblind trainings and for the phase corrections of blind trainings, 3 CAZAC sequences of 64 symbols are used. The transmitter repeats the transmission of the same packets for each measurement point; however, the payload data changes for every new packet in the simulations.
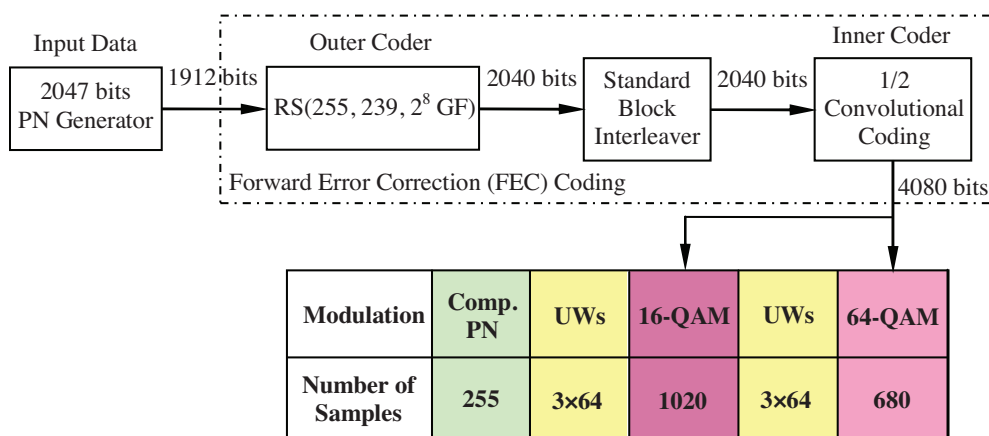

Figure 2. Transmit data packet structure.

A vector signal analyzer (WCA380 from Tektronix, 0-8 GHz) was used in the receiver of the experimental RF radio. The baseband of the received signal was sampled at a sampling frequency of 20.48 Msamples/s and stored by the analyzer with a length of 100 experimental data sequences, as given in Figure 2. This sampled long sequence was downloaded to a PC for the baseband signal processing and BER calculations. A receiver algorithm, involving synchronization, equalization, and decoding, was implemented in a program written in C programming language.

The error count was made after equalization for the raw BER calculations of the system without a coding gain. The equalized data were decoded by an inner decoder, deinterleaved, and decoded again by the outer decoder. The final error count was obtained over the decoded data in order to obtain the overall BER performance of the system. Here, the error rates of all modulation types were calculated at one measurement point, the single trail of the channel. Thus, in order to obtain an average value, as is done in Monte Carlo simulation programs, an averaging process was required, which is explained in the following section.

BER performance results were obtained on the grid shown in Figure 3, and the effects of the modulation types were compared using the same channel. Therefore, a measurement grid of 100 points and a minimum

distance between measurements points of 8.5 cm, the approximated wavelength of the carrier, were chosen. The physical placement of the grid is shown in Figure 3. The obtained BER performance was thus the averaged value over 100 separate channels with a similar expected signal-to-noise ratio (SNR) value. The highest measured SNR value, 25 dB for 16-QAM and 64-QAM, was the starting point for the BER performance analysis. The rest of the analyses were carried out by adding the sampled noise sequence to the received signal in order to obtain the BER values for lower SNR levels. For different levels of SNR, the noise sequence was multiplied by a constant, which was adjusted according to the desired SNR level before adding the noise sequence to the received data sequence.
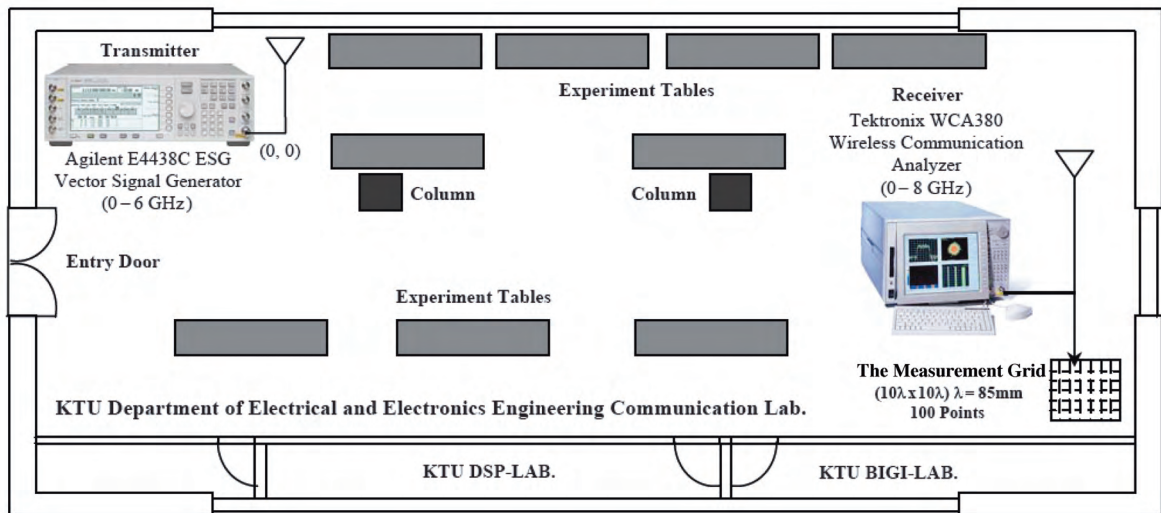

Figure 3. The test area and measurement grid with 100 points.

4. Theoretical and experimental simulation results

In this study, 4 methods of blind equalizer trainings, conventional CMA, M-CMA, N-CMA, and F-CMA, and 2 conventional adaptive training algorithms for nonblind trainings, LMS and RLS, were employed for equalizations of experimental received data and in simulations. An 11-tap LTE filter was used in both blind and nonblind training methods. The center tap of the LTE was set to unit value in blind trainings; otherwise, the values of all taps were initialized to zero before starting the training. Table 2 shows the step-size parameters of the blind training methods. The step-size parameter for LMS was 0.0025 for 16-QAM and 0.00015 for 64-QAM, and the forgetting factor of RLS was 0.999 for both 16-QAM and 64-QAM. The given training parameters were used in both experimental and simulation data. The nonblind trainings, LMS and RLS, were carried out using all 3 CAZAC sequences at the beginning of each assigned subsequence. Thus, 1152 (6×192) and 1920 (10×192) steps of nonblind training were executed before starting the recovery of incoming data for the attained 16-QAM and 64-QAM modulation types, respectively.

Table 2. Algorithm parameter settings in simulation.

Modulation	CMA	M-CMA		N-CMA	
type	μ_{CMA}	μ_{MCMA}	a	α	σ
16-QAM	0.00115	0.005	0.42	0.0025	0.086
64-QAM	0.00005	0.00032	0.075	0.0014	0.092

The blind equalizations were completed in 4 steps. First, the beginning of each subsequence was defined in the received data sequence. Second, the blind training was carried out over the entire length of each subsequence (4080 (4 × 1020) steps for 16-QAM and 6800 (10 × 680) steps for 64-QAM). Third, the ISI was cancelled by running the blindly trained equalizer filter over the CAZAC sequences and the received data for each subsequence. Fourth and finally, the phase correction coefficient was obtained using the CAZAC sequences at the beginning of the subsequence, as in [19], and the phase correction of the related subsequence was done before the detection and decoding of the subsequence.

Figure 4 shows sampled channel profiles with 7 taps observed above the noise floor of the receiver used in the experiments, at the first row of the measurement grid shown in Figure 3.
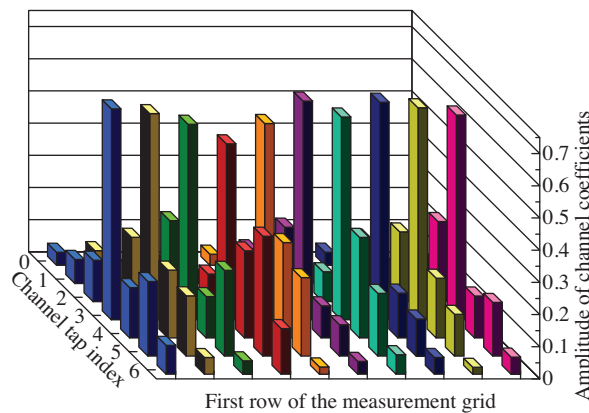

Figure 4. A sampled channel profile obtained from the experimental radio.

The obtained BER performances of the blind trainings, CMA, M-CMA, N-CMA, and F-CMA, for simulated and experimental channel equalizations are given in Figures 5 and 6 for 16-QAM and 64-QAM, respectively, where 239/256 Reed-Solomon and 1/2 convolutional coding were employed in the cascade, as explained in [1]. The dashed lines belong to the simulation performances of equalizations using the channel profile given by (0.407, 0.815, 0.407), which is defined in [20]. The experimental data produced worse performances, by around 1.5 to 2 dB, than the simulated channels' data, since the channel delay spreads grew quite larger at some measurement points, as shown in Figure 4.

Figure 5 compares the BER performances of 4 blind equalizers for 16-QAM. The performance of N-CMA was a little better than the performances of the conventional CMA, but the obtained result was not remarkable. M-CMA performed better than conventional CMA and N-CMA, and it also converged to the lower BER floor value of 1E-2. However, F-CMA, improved in [14,15], provided a satisfactory performance and outperformed the other blind equalizers, conventional CMA, M-CMA, and N-CMA. The simulation results demonstrated that the theoretical and experimental studies were compatible with each other.

Figure 6 also compares the BER performances of 4 blind equalizers for 64-QAM. The performances of M-CMA and N-CMA were better than the performance of the conventional CMA after approximately 10 dB of SNR, and converged to lower than the BER value of 2E-1. However, F-CMA outperformed all of the simulated blind equalization algorithms in this study.

The obtained comparative BER performances of nonblind trainings, LMS and RLS, and blind trainings, CMA, M-CMA, N-CMA, and F-CMA, for simulated and experimental channel equalizations are given in Figures 7 and 8 for 16-QAM and 64-QAM, respectively.
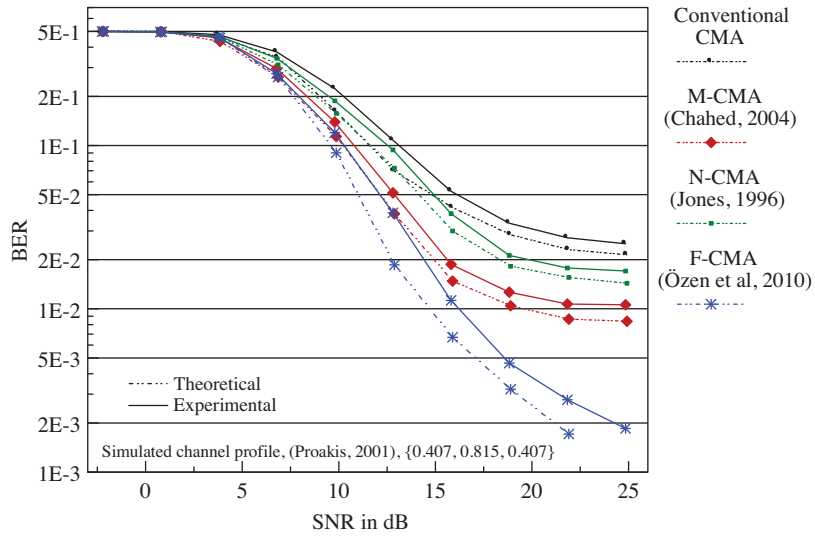
Figure 5. BER performances of blind equalizers for 16-QAM modulation.
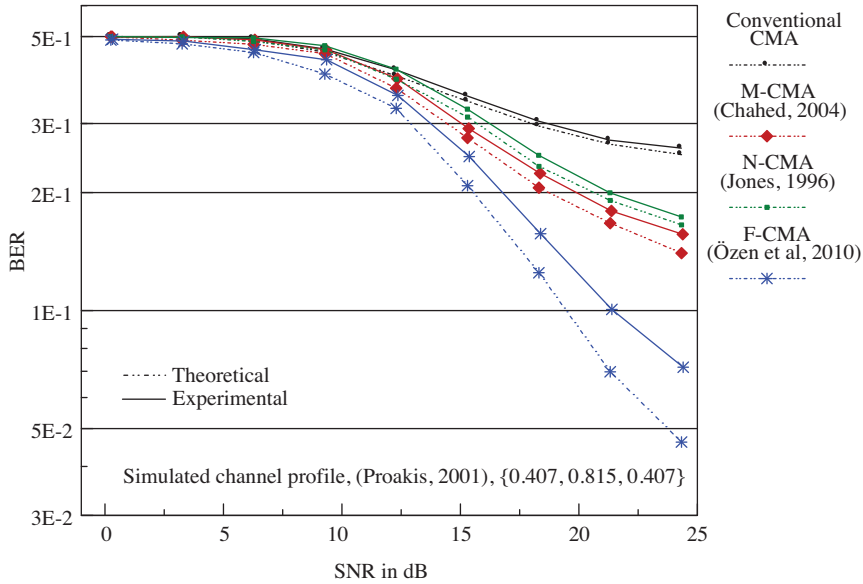

Figure 6. BER performances of blind equalizers for 64-QAM modulation.

This is among the first experimental studies of blind equalizations to find that the performances of nonblind equalizations are from 3 to 5 dB better than the considered blind equalization techniques. When the performances of the 16-QAM modulation are considered, the RLS training is around 2 dB better than the LMS; however, both algorithms were able to clear the error region below 22.5 dB of the SNR. Of course, the coding helps the LMS trainings much more than the RLS. The simplicity of the LMS algorithm can then easily lead to encouragement of LMS as the best candidate for a real-time application. However, the blind trainings are not too far behind, especially as F-CMA also canceled the error floor around 20 dB SNR and its performance was quite solid for 16-QAM.
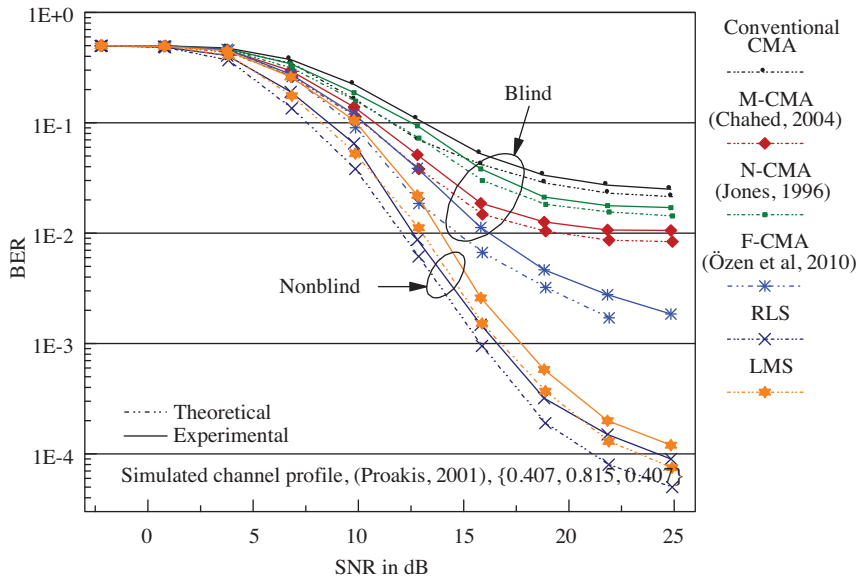
Figure 7. BER performance comparisons of nonblind and blind equalizers for 16-QAM modulation.
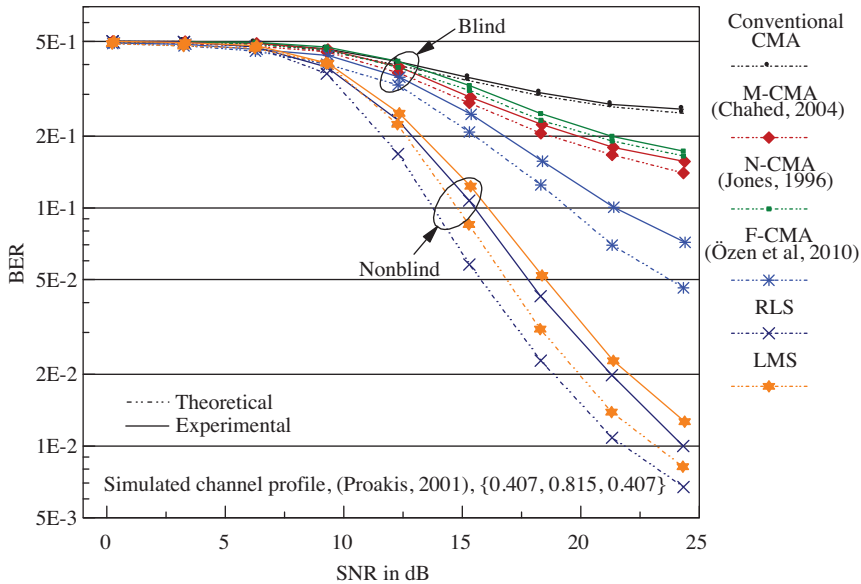

Figure 8. BER performance comparisons of nonblind and blind equalizers for 64-QAM modulation.

For 64-QAM modulation, the obtained performances of the blind equalizations started to vary, since CMA, M-CMA, and N-CMA produce an error floor in both experimental and simulated channels while the BER curves of F-CMA outperformed all simulated blind equalization algorithms in this study. The performance gap between nonblind and blind trainings in 64-QAM was from 6 to 8 dB, as shown in Figure 8.

5. Conclusion

This study compared the BER performances of adaptive equalizations using blind and nonblind training techniques in order to obtain a comprehensive performance profile in experimental and simulated wireless

communication channels for high-order QAM signaling. Instead of using a certain type of channel profile, this study concentrated on true frequency-selective Rayleigh fading channels and also evaluated the fast fading scenario of Rayleigh channels in a real-time WiMAX radio environment around 3.5 GHz. The popular LMS algorithm and CMA were used as benchmarks in an investigation of nonblind and blind training techniques, namely RLS, M-CMA, N-CMA, and F-CMA. The obtained simulation results demonstrated that the nonblind training methods have considerably better performance than the blind training methods.

Acknowledgements

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