International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161

Available at http://inpressco.com/category/ijcet

Research Article

Semi Blind Channel Estimation with Training-Based Pilot in AF Two-Way Relaying Networks

Hemant Gavaskar*and Sandeep Kumar Agrawal

Dept. of ECE Department, RGPV University, Rustamji Institute of Technology BSF Academy Tekanpur, Gwalior, M.P, India

Accepted 20 Jan 2017, Available online 30 Jan 2017, **Vol.7, No.1 (Feb 2017)**

Abstract

2-way relaying networks are design for bandwidth efficient use of the available spectrum, since it allow for data exchange between two users with the involvement of an intermediate relay node. Due to superposition of signals in the relay node, the received signal at the user terminals is affected by multiple parameters like channel gains, timing offsets, and carrier frequency offsets which need to be estimate and compensate. Our proposed semi-blind estimator is based on the Gaussian maximum likelihood criterion which treats that data symbols as Gaussian-distributed nuisance parameters. To assist in the estimation of the individual channels, we adopt a superimposed training strategy at the relay. We have design the pilot vectors of the terminals and the relay to optimize the estimation performance. Moreover it we compare the semi-blind and pilot-based Cramer-Rao bounds (CRBs) to use as performance benchmarks. We use simulation result to show that the proposed method provides improvement in estimation accuracy over the conventional pilot-based estimation and it approaches the semi-blind CRB as SNR increases & the simulation results shows that the performance of the proposed estimators is related to the derived CRLBs at moderate to high SNR. It is also shows that the overall BER performance of the AF TWRN is close to a TWRN.

Keywords: *Mean square Error(MSE) ,Cramer-Rao lower bounds (CRLB), Bit-error Rate(BER) Gaussian maximum likelihood criterion, Amplify and Forward (AF).*

1. Introduction

Relaying is the key technology to relate the communication between two user terminals, especially when there are large distances between them (B. Rankov and A. Wittneben Feb. 2007). Unidirectional or one-way relaying supports in communication from a source to a destination user and has been studied in the literature (B. Rankov and A. Wittneben Feb. 2007). On the other hand, in two-way relaying networks (TWRNs), the flow of information is bidirectional and the two users exchange data simultaneously with the relation of an intermediate relay node (S. Abdallah and I. N. Psaromiligkos(Jul. 2012). The comparison with one-way half-duplex relaying, bidirectional relaying is a spectrally more efficient relaying protocol (S. Abdallah and I. N. Psaromiligkos(Jul. 2012). Both amplify-and-forward and decode-and-forward protocols have been designed for TWRNs. If comparison to the DF protocol & AF protocol is widely adopted, as it requires minimal processing at the relay node (F. Gao, R. Zhang, and Y. Liang,Oct. 2009) .The two phase communications in AF TWRNs, the two users firstly transmit data to the relay node than relay broadcasts its receive signal to both users in the second in phase1 the two users signals at the relay node under different propagation paths and may not be aligned in time and frequency. The superimposed signal broadcasted from the relay node is affected by multiple impairments examples are channel gains, timing offsets & CFO. The estimation and compensation algorithms have been applied to counter these impaired in unidirectional relaying networks (F. Gao, R. Zhang, and Y. Liang,Nov. 2009), (G. Wang, F. Gao, Y. C. Wu, and C. Tellambura, Feb. 2011.) the proposed algorithms cannot be directly applied to TWRNs due to differences between the two system models.

In TWRNs Fig. 1, each user can exploit the knowledge of the self transmitted signal during Phase 1 in order to detect the signal from the other user during Phase 2. The blind (G. Wang, F. Gao, Z. X., and C. Tellambura, 2010) & semi-blind (G. Wang, F. Gao, W. Chen, and C. Tellambura, Aug. 2011) methods have been proposed for channel estimation only in AF TWRNs. A particle filtering based method for estimating channel and timing offset is used in (X. Liao, L. Fan, and F. Gao, *2010*). In training based methods, which are more for practical implementation (E. de Carvalho and D. T. Slock, Apr. 2004.), channel estimation (F. Gao, R. Zhang, and Y. Liang,Oct. 2009), (T.-H. Pham, Y.-C. Liang, H. Garg, and A.

*Corresponding author **Hemant Gavaskar** is a PG Student **and Sandeep Kumar Agrawal** is working as Professor

Nallanathan,2010) or joint channel and CFO estimation (G. Wang, F. Gao, and C. Tellambura,2010) has been considered in the literature. The best of author's knowledge, estimation and decoding scheme for TWRNs in the presence of channel gains, timing offsets, and CFO is still an open research problem. In this paper, a complete synchronization approach, i.e., joint estimation and compensation of channel gains, timing offsets, and CFO for AF TWRNs is proposed. The reception of mixed in signals broadcasted from relay node, the user nodes first jointly estimate the impairments using known training signals and the proposed ML algorithm or differential evolution based estimators (S. Zhang, F. Gao, and C. Pei,Sep. 2012). Subsequently, the users employ the proposed minimum mean-square error receiver in combination with the estimated impairments to decode the received signal. The contributions of this paper can be summarized as follows:

- We design a system model for having synchronization and set the channel parameters in AF TWRN.
- We assign Cramer-Rao lower bounds for joint estimation of multiple impairments at the user nodes for TWRN. These bounds can be applied to have the performance of synchronization and channel estimation in AF TWRN networks.
- We derive an ML based estimator for joint estimation of multiple impairments. A DE based algorithm is designed for an alternate of ML estimator to reduce the complexity with synchronize in AF TWRNs. Simulation results show that the mean square error performances of both ML and DE estimators are close to the CRLB at moderate to-high S/N ratios.
- We have an MMSE receiver for compensating the impairments and detecting the signal from the opposing user. The simulations are carried out to measure the estimated MSE and BER performances of the proposed transceiver structure. These results show that BER performance of an AF TWRN can be improved in the presence of practical synchronization errors. In fact, the application of the derive transceiver results in an overall network efficiency which is very close to the ideal network based on the assumption of knowledge of synchronization and channel parameters.

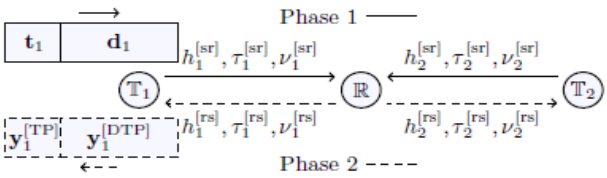

Fig.1 System Model for AF two-way relay network

Notation: Superscripts $(.)^T$, $(.)^*$, and $(.)^H$ denotes the transpose, the conjugate, and the conjugate transpose operators, respectively. $\Xi_X\{.\}$ denotes the expectation operator with respect to the variable x. The operator $\hat{x}$ represents the estimated value of x. $\Re\{.\}$ & $\xi\{.\}$ denote the real and imaginary parts of a complex quantity. $CN(\mu,\sigma^2)$ denotes the complex Gaussian distributions with mean μ and variance σ^2 . Boldface small letters, x and boldface capital letters, **X** are used for vectors matrices, respectively. $[\mathbf{X}]_{x;y}$ represents the entry in row x and column y of **X**. $\mathbf{I}_X$ denotes X×X identity matrix, ‖x‖ represents the ⌊ 2 norm of a vector x, and diag(x) is used to denote a diagonal matrix, where its diagonal elements are given by the vector x.

2. System Model

We consider a half-duplex AF TWRN with two user terminals, T1 and T2, and a relay node, R, as shown in Fig. 1.All nodes are equipped with a single omnidirectional antenna. The channel gain, timing offset, and carrier frequency offset between the k_{th} user terminal and the relay node are denoted by h_k, τ_k and ν_k, respectively, for k = 1, 2, where the superscripts, $(.)^{[sr]}$ and $(.)^{[rs]}$, are used for the parameters from user terminal to relay node and from relay node to user terminal, respectively. The timing and carrier frequency offsets are modeled as unknown deterministic parameters over the frame length, which is similar to the approach adopted in (E. de Carvalho and D. T. Slock,Apr. 2004) and (B. Rankov and A. Wittneben Feb. 2007). Quasi-static and frequency flat fading channels are considered, i.e., the channel gains do not change over the length of a frame but change from frame to frame according to a complex Gaussian distribution, CN $(0,\sigma_h^2)$. The use of such channels is motivated by the prior research in this field (S. Abdallah and I. N. Psaromiligkos, Jul. 2012), (T.-H. Pham, Y.-C. Liang, H. Garg, and A. Nallanathan,2010)].The transmission frame from each user is comprised of training and data symbols. The exchange of data among the two user terminals is completed in two phases:

1) During the first phase, the transmission frame, $[t_k; d_k]$, is transmitted from the k_{th} user, = 1,2 to an intermediate relay node, where t_k and $d_k$denote the k_{th} user's training and data signal, respectively. This is illustrated in Fig. 1. The signal from the two users is superimposed at the relay node.
2) During the second phase, the relay node amplifies the superimposed signal and broadcasts it back to the users. The users use the training part of the received signal, $y_k^{[TP]}$, to jointly estimate the multiple impairments, i.e, channel gains, timing offsets, and carrier frequency offsets. The effect of these impairments is compensated and the received signal, $y_k^{[DTP]}$, is decoded at the k_{th}user's terminal.

Note: that the superscripts $(.)^{[TP]}$ and $(.)^{[DTP]}$ denote the signals in training and data transmission periods,

respectively and Fig. 1 shows the transmitted frames at the first user terminal, T1. A similar structure is followed for the second user terminal, T2. The received signal at the relay node during the training period, $r^{[TP]}(t)$, is given by

$$r^{[TP]}(t)=\sum_{k=1}^{2} h_k^{[sr]} e^{j2\pi\frac{v_k^{[rs]}}{T}t} \sum_{n=0}^{L-1} t_k(n) g(t-nT-\tau_k^{[sr]}T)+n(t) \quad (1)$$

where the timing and carrier frequency offsets, $\tau_k^{[SR]}$ and $v_k^{[SR]}$,are normalized by the symbol duration T, L is the length of training signal t_k, g(t) stands for the root-raised cosine pulse function, and n(t) denotes zero-mean complex additive white Gaussian noise (AWGN) at the relay receiver, i.e., $n(t)\approx CN(0,\sigma^2)$. To avoid amplifier saturation at the relay, the relay node amplifies the received signal, $r^{[TP]}(t)$, with the power constraint factor, $\xi=\frac{1}{\sqrt{2\sigma_h^2+\sigma_n^2}}$, and broadcasts the amplified signal to the users (F. Roemer and M. Haardt, Nov. 2010). The received signal at the user terminal, T1, during the training period, $y^{[TP]}(t)$ is given by

$$y_1^{[TP]}(t)=\zeta h_1^{[rs]} e^{j2\pi\frac{v_1^{[rs]}}{T}t} r^{[TP]}(T-\tau_1^{[rs]}T)+w_1(t), \quad (2)$$

where $w_1(t)$ denotes the zero-mean complex AWGN at the receiver of T_1, i.e. $w_1(t)\approx CN(0,\sigma_w^2)$ Substituting (1) into (2), $y^{[TP]}(t)$ is given by

$$y_1^{[TP]}(t)=\zeta h_1^{[rs]} e^{j2\pi\frac{v_1^{[rs]}}{T}t} \sum_{k=1}^{2}(h_k^{[sr]} e^{j2\pi\frac{v_k^{[sr]}}{T}(t-\tau_1^{[rs]}T)})\times\sum_{n=0}^{L-1} t_k(n) g(t-nT-\tau_k^{[rs]}T-\tau_1^{[rs]}T))$$
$$+\zeta h_1^{[rs]} e^{j2\pi\frac{v_1^{[rs]}}{T}t} n(T-\tau_1^{[rs]}T)+w_1(t), \quad (3)$$

Note that unlike, the developed system model in (3) takes into account both the timing errors, from users to the relay node, $\tau_k^{[SR]}$, k = 1; 2, and from relay node back to user terminal T1, $\tau_1^{[SR]}$. The received signal in (3), $y_k^{[TP]}(t)$, is sampled with the sampling time T_s = T/Q and the sampled received signal, $y_1^{[TP]}(i)$, is given by

$$y_1^{[TP]}(t)=\sum_{k=1}^{2} \alpha_k^{[sr]} e^{j2\pi v_k i/Q}\times\sum_{n=0}^{L-1} t_k(n) g(iT_s-nT-\tau_k^{[rs]}T)$$
$$+\zeta h_1^{[rs]} e^{j2\pi v_1^{[rs]} i/Q} n(i)+w_1(t) \quad (4)$$

Where

- $\alpha_k \triangleq \zeta h_k^{[sr]} h_1^{[rs]} e^{-j2\pi v_k^{[sr]}\tau_1^{[rs]}}$ is the combined channel gain from T1-R-T1 and T2-R-T1 for k = 1 and k = 2,respectively,
- $v_k \triangleq v_k^{[sr]}+v_1^{[rs]}$ is the sum of carrier frequency offsets from T1-R-T1 and T2-R-T1 for k = 1 and k = 2, respectively, $v_1^{[rs]}=-v_k^{[rs]}$ because same oscillators are used during transmission from user T1 to the relay node and from relay node back to user T1, thus, $v_k = v_k^{[sr]}+v_1^{[rs]}$ =0,
- $\tau_k \triangleq \tau_k^{[sr]}+\tau_1^{[rs]}$ is the resultant timing offset from T1-R-T1 and T2-R-T1 for k = 1 and k = 2, respectively,

Q is the sampling factor, n = 0, 1,……L- 1 and i = 0, 1,……..LQ - 1 are used to denote T-spaced and T_s spaced samples, respectively, and n(i) has been used in place of n(iT_s - $\tau_k^{[sr]}T$]), since n(t) denotes the AWGN and its statistics are not affected by time delays. Upon reception of signal broadcasted from the relay, it is assumed that the users first employ coarse frame synchronization to ensure that the superimposed signals are within one symbol duration from each other Eq. (4) can be written in vector form as

$$y_1^{[TP]}=\alpha_1 G_1 t_1+\alpha_2\Lambda_2 G_2 t_2+\zeta h_1^{[rs]}\Lambda^{[rs]} n+w_1 \quad (5)$$

Where

- $\mathbf{G}_k$ is the LQ × L matrix of the sample of the pulse shaping filter such that $[G_k]_{i,n} \triangleq g_{rrc}(iT_S-nT-\tau_k^{[rd]}T)$,
- $\Lambda_2 \triangleq diag([e^{j2\pi v_2(0)/N},\ldots\ldots,e^{j2\pi v_2(LQ-1)/N}])$ is an LQ×LQ matrix,
- $\Lambda^{[rs]} \triangleq diag([e^{j2\pi v_2(0)/N},\ldots\ldots,e^{j2\pi v_2(LQ-1)/N}])$ is an LQ×LQ matrix,
- $y_1^{[TP]} \triangleq diag[y_1^{[TP]}(0),\ldots\ldots,y_1^{[TP]}(LQ-1)]^T$
- $t_k \triangleq [t_k(0),\ldots\ldots,t_k(LQ-1)]^T$,
- $n \triangleq [n(0),\ldots\ldots,n(LQ-1)]^T$ and
- $w_1 \triangleq [w_1(0),\ldots\ldots,w_1(LQ-1)]^T$.

The received signal during the data transmission period $y_1^{[DTP]}$,can be similarly expressed as (5), where training $t_k$is replaced by the data d_k =[d_k(0),…….. d_k(L - 1)]^T . Note that as anticipated, the data length L is different and larger than the training length L Without loss in generality,we derive the CRLB and estimators for joint estimation of channel gains, timing offsets, and CFO at the user terminal T_1.The system model in this part and the derived CRLB, estimation, and detection schemes in these sections can be easily manipulated to detect d_1 at the user terminal T_2. These details are not included to avoid repetition.

3. Semi-Blind Channel Estimation

We present the proposed semi-blind channel estimation algorithm. For comparison purposes, we also consider fully pilot-based estimation and derive the corresponding Pilot-based least-squares (LS) channel estimator.

A. the CRB for Pilot-based Estimation

This technique combines the effort of both pilot-assisted estimation technique and blind estimation techniques, where the intrinsic information in the unknown data symbols and the known pilot information are used for channel estimation. Using the same number of pilot symbols, semi-blind estimation techniques perform better than pilot based techniques. Semi-blind techniques solve the uncertainty problem associated with blind estimation using few pilot symbols. Some literatures have investigated semi-blind estimation using the subspace method. According to (G. Wang, F. Gao, Z. X., and C. Tellambura, 2010), there is high computational complexity associated with the subspace method. Also, in the study in (X. Liao, L. Fan, and F. Gao, *2010*), linear prediction was used to estimate the blind constraint while the matrix A was estimated using the least square (LS) algorithm. The use of semi-blind channel estimation in single input multiple output (SIMO) systems achieved good performance using the subspace method and it has a simple structure (G. Wang, F. Gao, W. Chen, and C. Tellambura, Aug. 2011) but its application in multiple inputs multiple output (MIMO) system is not too successful because it can only estimate channel subject to a polynomial matrix ambiguity (G. Wang, F. Gao, W. Chen, and C. Tellambura, Aug. 2011).

B. The CRB for Semi-blind Estimation

Some other literature state that estimations are based on second-ordered statistics of a long vector, therefore there is need for a large number of OFDM symbols to estimate the correlation matrix and this is not suitable for fast time-varying channels. According to the subspace method is not practical for general MIMO channel estimation. The subspace algorithm in is limited to MIMO OFDM systems. It analyses the various semi blind channel estimation having the estimation on MIMO systems. Parallel data and training signal algorithm is developed, block recoded space time OFDM transmission is presented. The least square estimator based on known pilot sequence is analyzed in and the statistical structure of the observation is used in the estimation. The first and second order statistic is used in to estimate the channel.

4. Cramer-Rao Lower Bound

In this section, the CRLB for joint estimation of multiple impairments at T1 are derived. The signal model in (5) can be rewritten as

$$y_1^{TP} = \Omega\alpha + u_1 \tag{6}$$

Where $\Omega \triangleq |G_1 t_1 \Lambda G_2 t_2|$ is an LQ×2 matrix, $\alpha \triangleq |\alpha_1, \alpha_2|$ and u $\triangleq \xi h_1^{[rs]} \Lambda^{[rs]} n + w_1$, based on assumption and proposed system model, the received signal vector, y_1^{TP}, is a circularly symmetric complex Gaussian random variable, $y_1^{[TP]} = CN(\mu_1, \sum)$, with mean μ and covariance matrix $\sum$ .given by

$$= \mu = \Omega\alpha \tag{7a}$$

and

$$\sum = \mathrm{E}\{u, u^H\} = (\xi\sigma_h^2\sigma_n^2 + \sigma_w^2) I_{LQ} = \sigma_u^2 I_{LQ}, \tag{7b}$$

Respectively. To determine the CRLB, we have to first formulate the parameter vector of interest. The user T1 has to estimate the channel gains α, timing offsets $\tau \triangleq [\tau_1, \tau_2]^T$, and the carrier frequency offset v_2. There is no need to estimate v_1 as this is found to be 0 as explained below (4).As a result, the parameter vector of interest, λ, is given by

$$\lambda = \triangleq \left[\Re\{\alpha\}^T, \xi\{\alpha\}^T, v_2, \tau^T\right]^T \tag{8}$$

Finally, the CRLB for the estimation of λ is given by the diagonal elements of the inverse of F. Note that the CRLB for channel estimation is the sum of the CRLBs for real and imaginary parts of the channel estimation.

5. Simulation Result

In this section, we investigate through simulations the performance of the proposed semi-blind algorithm and compare it to that of the pilot-based LS estimator.

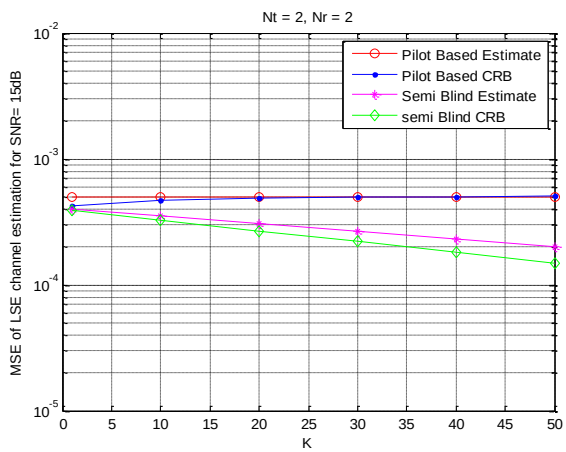

Fig.2MSE performance of the semi-blind and pilot-based (LS) estimators along with the corresponding semi-blind and pilot-based CRBs plotted versus K for the cases of Gaussian-distributed and QPSK-distributed data symbols

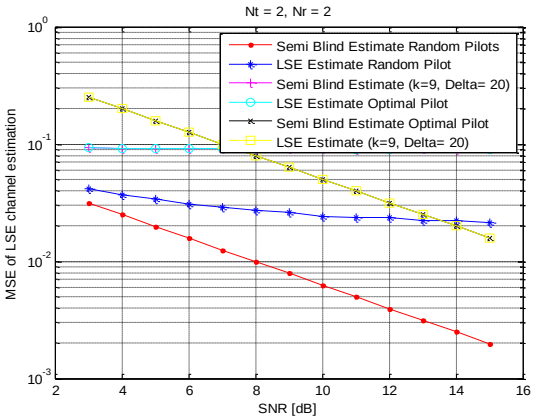

Fig.3MSE performance of the LS estimator and the semi-blind estimator versus SNR (L = 10, N = 32) for three scenarios: 1) optimal pilots (κ = 9,δ= 20), 2) suboptimal pilots (κ = 9, δ = 15) and 3) randomly generated pilots

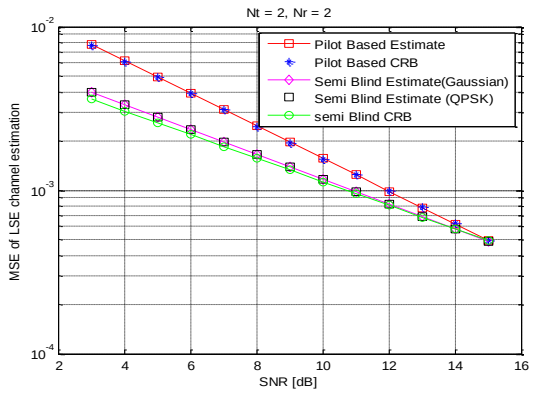

Fig.4MSE performance of the semi-blind and pilot-based (LS) estimators along with the corresponding semi-blind and pilot-based CRBs plotted versus SNR for the cases of Gaussian-distibuted and QPSK-distributed data symbols

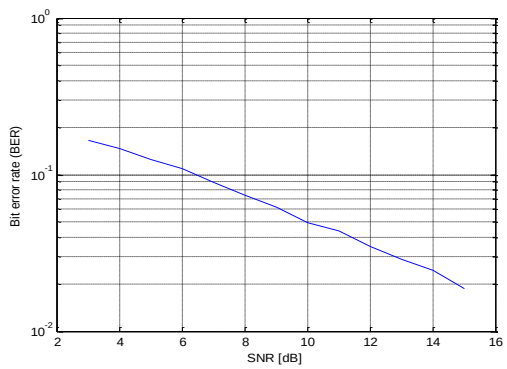

Fig.5 Bit error rate (BER) v/s SNR

Conclusion

In this paper, we proposed a semi-blind channel estimator for OFDM-based AF TWRNs based on the Gaussian ML approach. To assist in the estimation of the individual channels, we employed superimposed training at the relay. In above Fig 2, we have a comparison between CRB based techniques such techniques are pilot based estimation, pilot based CRB, semi blind estimation and semi blind CRB. We found that SNR increase along with x-axis and MSE level decreases along with y-axis and semi blind CRB technique provides better result as compared to the other CRB based techniques. In above Fig 3, we have comparison in semi blind estimation random & optimal pilot, LSE estimation random & optimal pilot. In which semi blind estimate random pilot provide better result as compare to other technique. As we increase SNR along X-axis MSE get reduce along Y-axis. In above Fig 4, we have compare pilot based estimate & CRB, Semi blind estimate & CRB along by using Gaussian and QPSK modulation technique. In which semi blind estimate provide better result as compare to other technique. As we increase SNR along X-axis MSE get reduce along Y-axis. In above Fig 5, Comparison between BER & SNR, In which bit error rate get reduce along Y-axis as we increase SNR along X-axis. The resulting GML estimates were obtained numerically using the BFGS algorithm. We also derived conditions for the optimality of the training pilots and provided examples of pilot vectors that satisfy them. As performance benchmarks, we derived the semi-blind and pilot-based CRBs. We used simulation studies to compare the proposed semi-blind estimator to the conventional pilot-based estimator and showed that the proposed estimator provides a substantial improvement in accuracy. The performance of the semi-blind algorithm closely approaches the derived semi-blind CRB as SNR increases. Finally, these performance gains can be achieved at a reasonable computational cost, which clearly establishes the merit and practicality of semi-blind channel estimation for AF TWRNs.

References

B. Rankov and A. Wittneben (Feb. 2007),Spectral efficient protocols for halfduplex fading relay channels,*IEEE J. Sel. Areas Commun.*, vol. 25, no. 2, pp. 379–389 .

S. Abdallah and I. N. Psaromiligkos(Jul. 2012),Blind channel estimation for amplify-and-forward two-way relay networks employing M-PSK modulation,*IEEE Trans. Signal Process.*, vol. 60, no. 7, pp. 3604–3615.

F. Gao, R. Zhang, and Y. Liang,(Oct. 2009), Optimal channel estimation and training design for two-way relay networks, *IEEE Trans. Commun.*,vol. 57, no. 10, pp. 3024–3033.

F. Roemer and M. Haardt,(Nov. 2010), Tensor-based channel estimation (TENCE) and iterative refinements for two-way relaying with multiple antennas and spatial reuse, *IEEE Trans. Signal Process.*, vol. 58, no. 11, pp. 5720–5735.

F. Gao, R. Zhang, and Y. Liang,(Nov. 2009),Channel estimation for OFDM modulated two-way relay networks,*IEEE Trans. Signal Process.*, vol. 57, no. 11, pp. 4443–4455,.

G. Wang, F. Gao, Y. C. Wu, and C. Tellambura,(Feb. 2011.), Joint CFO and channel estimation for OFDM-based two-way relay networks, *IEEE Trans. Wireless Commun.*, vol. 10, no. 2, pp. 456–465.

G. Wang, F. Gao, Z. X., and C. Tellambura (2010) Superimposed training based joint CFO and channel estimation for CP-OFDM modulated two way relay networks, *EURASIP J. Wireless Commun. and Network.*, vol.2010, ID=403936.

G. Wang, F. Gao, W. Chen, and C. Tellambura (Aug. 2011) Channel estimation and training design for two-way relay networks in time-selective fading environments, *IEEE Trans. Wireless Commun.*, vol. 10, no. 8, pp. 2681–2691.

X. Liao, L. Fan, and F. Gao,(*2010*) Blind channel estimation for OFDM modulated two-way relay network, in *Proc. 2010 IEEE Wireless Comm.and Networking Conf.*

E. de Carvalho and D. T. Slock (Apr. 2004.) Blind and semi-blind FIR multichannel estimation: (global) identifiability conditions, *IEEE Trans. Signal Process.*, vol. 52, no. 4, pp. 1053–1064,

S. Abdallah and I. N. Psaromiligkos (Jul. 2012) Exact Cramer-Rao bounds for semi-blind channel estimation in amplify-and-forward two-way relay networks employing square QAM modulation, ArXiv pre-print cs.IT/1207.5483,

T.-H. Pham, Y.-C. Liang, H. Garg, and A. Nallanathan (2010) Joint channel estimation and data detection for MIMO-OFDM two-way relay networks, in *Proc. 2010 IEEE Global Comm. Conf.*

G. Wang, F. Gao, and C. Tellambura (2010) Superimposed pilot-based joint CFO and channel estimation for CP-OFDM modulated two-way relay networks, in *Proc. 2010 IEEE Global Comm. Conf.*

S. Zhang, F. Gao, and C. Pei (Sep. 2012) Optimal training design for individual channel estimation in two-way relay networks,*IEEE Trans. Signal Process.*, vol. 60, no. 9, pp. 4987–4991.

K. Lee, H. Sung, E. Park, and I. Lee (Dec. 2010) Joint optimization for one and two-way MIMO af multiple-relay systems*, IEEE Trans. Wireless Commun*., vol. 9, no. 12, pp. 3671–3681.

S. Abdallah and I. N. Psaromiligkos (Jul. 2012) Blind channel estimation for amplify-and-forward two-way relay networks employing M-PSK modulation, *IEEE Trans. Signal Process*., vol. 60, no. 7, pp. 3604–3615.

F. Roemer and M. Haardt,(Nov. 2010) Tensor-based channel estimation (TENCE) and iterative refinements for two-way relaying with multiple antennas and spatial reuse, *IEEE Trans. Signal Process*., vol. 58, no. 11, pp.5720–5735,.

N. Moller (Jan.2008) On Schoonhage's algorithm and subquadratic integer gcd computation, *Mathematics of Computation*, vol. 77, pp. 589–607,.

B. P. Singh and R. Singh (2006) Electronic devices and integrated circuits.*Pearson Education India*, 2006.