Available online at www.sciencedirect.com
ScienceDirect
Int. J. Electron. Commun. (AEÜ) 62 (2008) 754–761
International Journal of Electronics and Communications
www.elsevier.de/aeue

Optimal superimposed training for estimation of OFDM channels☆

Qinghai Yang*, Kyung Sup Kwak

UWB-ITRC, Graduate School of Information Technology and Telecommunications, Inha University, #253 Yonghyun-dong, Namgu, Incheon 402-751, Korea

Received 13 October 2006; accepted 29 September 2007

Abstract

We design an optimal superimposed training (SIT) scheme for orthogonal frequency division multiplexing (OFDM) systems. Linear minimum mean square error (MMSE) and least square (LS) channel estimator are developed. The proposed optimal SIT consists of two parts, optimal training sequences deduced with respect to the channel estimate's mean square error (MSE) and optimal power allocation between training and data derived by minimizing the averaged channel capacity lower bound. The relationship between bit error ratio (BER) and averaged capacity bound is investigated under the optimal SIT. Simulation results validate our optimum design.

Keywords: OFDM; Channel estimation; MMSE; LS; Superimprosed training

1. Introduction

Superimposed training (SIT)-aided channel estimation [1] has recently been proposed for wireless communications. The idea behind this method is that known-pilots are superimposed on data symbols at the transmitter, and at the receiver the channel can be estimated by using these superimposed pilots. The major advantage of this approach is no bandwidth wastage in contrast to a conventional pilot-assisted channel estimation method, wherein training pilots are time/frequency multiplexed with data symbols, leading to a data-rate reduction.

The performance of an SIT-aided channel estimation is affected by the embedded unknown data. Hence, endeavors to mitigate these effects have been taken up in literatures. For block-fading channels, the data-dependent sequence that is able to cancel those impacts was developed in [2], but it was only suitable for single-carrier transmissions. An algorithm proposed in [3] tried to diminish these effects by adopting the first-order statistics of the data. Based on iterative methods, a maximum a prior (MAP) algorithm was proposed in [4] by combining with a 2D channel estimator, and the algorithms of recursive least squares (RLS) and expectation maximization (EM) were studied in [5]. For fast fading channels, a Kalman tracking based SIT approach was investigated in [6], and a selective SIT scheme was proposed in [7]. In this paper, we consider a multi-carrier scenario-orthogonal frequency division multiplexing (OFDM) system, where training pilots are added to data symbols in the frequency domain [8,9].

In SIT schemes, the sum powers of pilot and data symbols are constrained by a fixed transmit-power budget. Consider a scenario where the data is detected by using estimated channel information at the receiver. Good data-detection performance requires highly accurate channel estimate which favors more transmit power assigned to pilots; but, more power allocated to pilots results in less leaving for data symbols, inversely causing degradation in data-detection performance. Hence, a power-allocation tradeoff between training

☆ This research was supported by the University IT Research Center Project (INHA UWB-ITRC), Korea.
* Corresponding author. Tel.: +82 32 864 8935; fax: +82 32 865 0480.
E-mail addresses: qhyang@inhaian.net (Q. Yang), kskwak@inha.ac.kr (K.S. Kwak).

1434-8411/$ - see front matter © 2007 Elsevier GmbH. All rights reserved.
doi:10.1016/j.aeue.2007.09.012

and data symbols becomes crucial. To obtain such an optimal power allocation solution, few results have ever appeared according to our best knowledge.

In this paper, we develop an optimal SIT scheme for OFDM channel estimates, which consists of two parts: the optimal SIT sequences and the optimal power allocation between training pilots and information data. Linear minimum mean square error (MMSE) and least square (LS) estimation of OFDM channels are developed by using SIT methods. Optimal SIT sequences are proposed by minimizing the trace of the channel estimates' mean square error (MSE) matrix. The lower bound of the averaged channel capacity is deduced with estimated channel information. The optimal power allocation between training pilot and data is derived in terms of maximizing the averaged capacity lower bound.

Notation: diag(.) represents the diagonal process and bdiag(.) the block diagonal process. $E\{.\}$ stands for expectation operator and $\delta(.)$ for Kronecker function; $\otimes$ denotes the Kronecker product; Vec($\mathbf{A}$) represents stacking the columns of matrix $\mathbf{A}$. $\mathbf{1}_{q\times p}$ denotes the all one matrix with dimension $p\times q$ and $\mathbf{I}_N$ an $N\times N$ identity matrix. Superscripts T, $*$, H denote transpose, conjugate and Hermitian, respectively.

2. Signal model

In OFDM systems, a serial data stream will be converted into parallel blocks of size K and each block is modulated by using an inverse fast Fourier transform (IFFT). Generally, symbols before modulation are referred as frequency-domain symbols, and symbols after modulation (passing IFFT) are called time-domain symbols. Define $s(k,n)$ as a frequency-domain symbol being transmitted on the kth subcarrier at time instance $n (n \in [0, N-1])$. In SIT schemes, $s(k,n)$ can be expressed as

$$s(k,n) = d(k,n) + c(k,n), \tag{1}$$

where $d(k,n)$ and $c(k,n)$ denote random data and known-pilot symbols, respectively, with averaged powers

$$\begin{cases} \rho_d = (1-\alpha)\bar{\rho}, \\ \rho_c = \alpha\bar{\rho}, \quad (0<\alpha<1). \end{cases} \tag{2}$$

Here, $\bar{\rho}$ denotes the averaged transmit power of $s(k,n)$ and α represents the power allocation fraction. In this paper, we assume that the random data symbols are zero mean, while with variance ρ_d.

At the receiver, the signal reconstructed in the frequency domain is given by

$$y(k,n) = H(k,n)[d(k,n) + c(k,n)] + z(k,n), \tag{3}$$

where $z(k,n)$ is complex-valued additive white Gaussian noise with zero-mean and variance σ_z^2; $H(k,n)$ denotes the discrete-time channel frequency response:

$$H(k,n) = \sum_{l=0}^{L} h(l,n)\mathrm{e}^{-\mathrm{j}2\pi lk/K}, \tag{4}$$

where $h(l,n)$ represents the channel impulse response of the lth path at time instance n and L denotes the number of nonzero paths. As a common approach, a cyclic prefix (CP) of length L will be inserted before transmission to eliminate inter-symbol interference. Let us write $\mathbf{h}(n) = (h(0,n),\ldots,h(L,n))^T$. Considering a wide-sense stationary-uncorrelated scattering (WSSUS) Rayleigh fading channel, the channel autocorrelation matrix can be expressed as

$$\mathbf{R_h} = E\{\mathbf{h}(n)\mathbf{h}^H(n)\} = \mathrm{diag}(\sigma_0^2,\ldots,\sigma_L^2), \tag{5}$$

where σ_l^2 denotes the channel power for the lth path.

3. Channel estimation

In this section, the linear MMSE and linear LS channel estimators are developed by using SIT pilots. Meanwhile, the optimal pilot sequences are proposed with respect to the channel estimate error. By using (4), the input–output relationship of (3) can be rewritten into

$$y(k,n) = [c(k,n)\mathbf{e}_k]\mathbf{h}(n) + v(k,n), \tag{6}$$

where $\mathbf{e}_k = (1,\ldots,\mathrm{e}^{-\mathrm{j}2\pi Lk/K})$ and $v(k,n) = H(k,n)d(k,n) + z(k,n)$. The cross-correlation of $v(k,n)$ can be derived as:

$$E\{v(k,n)v(k',n')^*\} = \sigma_v^2\delta(k-k')\delta(n-n'), \tag{7}$$

where $\sigma_v^2 = \rho_d\sum_l\sigma_l^2 + \sigma_z^2$. Thus, $v(k,n)$ can be viewed as additive white noise with zero mean and variance σ_v^2.

Assuming the channel variation is negligible within N OFDM symbol periods, the index n of $\mathbf{h}(n)$ can be omitted accordingly. Let us write $\mathbf{y} = (\mathbf{y}_0^T,\ldots,\mathbf{y}_{N-1}^T)^T$ with $\mathbf{y}_n = (y(0,n),\ldots,y(K-1,n))^T$. We have

$$\mathbf{y} = \mathbf{\Lambda\Gamma h} + \mathbf{v}, \tag{8}$$

where $\mathbf{\Lambda}$ is a $KN \times KN$ diagonal matrix defined as $\mathbf{\Lambda} = \mathrm{bdiag}(\Lambda_0,\ldots,\Lambda_{N-1})$ with $\Lambda_n = \mathrm{diag}(c(0,n),\ldots,c(K-1,n))$; $\mathbf{\Gamma} = \mathbf{1}_{N\times 1}\otimes\mathbf{F}_L$ with the kth row of $\mathbf{F}_L (K\times(L+1))$ being $\mathbf{e}_k$; $\mathbf{v}$ is obtained from the corresponding stack of $v(k,n), \forall k,n$, i.e.,

$$\mathbf{v} = \mathbf{Hd} + \mathbf{z}, \tag{9}$$

where $\mathbf{H} = \mathrm{bdiag}(\mathbf{H}_0,\ldots,\mathbf{H}_{N-1})$ with $\mathbf{H}_n = \mathrm{diag}(H(0,n),\ldots,H(K-1,n))$, $\mathbf{d} = (\mathbf{d}_0^T,\ldots,\mathbf{d}_{N-1}^T)^T$ with $\mathbf{d}_n = (d(0,n),\ldots,d(K-1,n))^T$ and $\mathbf{z} = (\mathbf{z}_0^T,\ldots,\mathbf{z}_{N-1}^T)^T$ with $\mathbf{z}_n = (z(0,n),\ldots,z(K-1,n))^T$. Following from (7), the covariance matrix of $\mathbf{v}$ can be easily obtained as $\sigma_v^2\mathbf{I}_{KN}$.

3.1. MMSE channel estimate

From (8), the linear MMSE channel estimate of $\mathbf{h}$ can be obtained as

$$\hat{\mathbf{h}}_{\mathrm{MMSE}} = (\sigma_v^2\mathbf{R_h}^{-1} + \mathbf{\Gamma}^H\mathbf{\Lambda}^H\mathbf{\Lambda\Gamma})^{-1}(\mathbf{\Gamma}^H\mathbf{\Lambda}^H)\mathbf{y}. \tag{10}$$