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Analysis of the Effect of Coherence Bandwidth on Leakage Suppression Methods for OFDM Channel Estimation

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Abstract

In this paper, we analyze the effect of the coherence bandwidth of wireless channels on leakage suppression methods for discrete Fourier transform (DFT)-based channel estimation in orthogonal frequency division multiplexing (OFDM) systems. Virtual carriers in an OFDM symbol cause orthogonality loss in DFT-based channel estimation, which is referred to as the leakage problem. In order to solve the leakage problem, optimal and suboptimal methods have already been proposed. However, according to our analysis, the performance of these methods highly depends on the coherence bandwidth of wireless channels. If some of the estimated channel frequency responses are placed outside the coherence bandwidth, a channel estimation error occurs and the entire performance worsens in spite of a high signal-to-noise ratio.

Index Terms: Coherence bandwidth, DFT-based channel estimation, Leakage, OFDM, Wireless channel

I. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) is a predominant transmission technology for ubiquitous wireless broadband networks because it can mitigate severe effects of frequency selective fading and provide good spectrum efficiency [1-4]. There have been many attempts to apply the multiple-input multiple-output (MIMO) technology to OFDM transmission systems, such as [5, 6].

For coherent detection of the received data symbols in OFDM transmission, channel frequency responses (CFRs) must be estimated and equalized. One of the OFDM channel estimation methods is pilot-aided channel estimation (PACE) where pilot symbols are assigned to pilot subcarriers, which are multiplexed with data subcarriers, and channel estimation for data symbols is performed by interpolation techniques. There are three basic factors affecting the performance of the PACE method. These are pilot patterns, estimation methods, and signal detection. The choice of these factors depends on OFDM system specifications and wireless channel conditions.

In PACE, CFRs at pilot subcarriers are estimated using least squares (LS) or minimum mean square error (MMSE) estimators, and then, interpolation techniques are performed in order to estimate CFRs at data subcarriers by using the estimated CFRs at pilot subcarriers, as shown in Fig. 1. As an interpolation technique of PACE methods, discrete Fourier transform (DFT)-based interpolation is often used.

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However, it may have the leakage problem caused by virtual carriers in an OFDM symbol. In order to deal with the leakage problem, some suppression methods were proposed in [7-11]. In particular, optimal and suboptimal linear estimators were proposed to estimate the equally spaced virtual carriers in [11], but whose performances are very sensitive to the coherence bandwidth of wireless channels. Therefore, in this study, optimal and suboptimal linear estimators are reviewed and theoretically analyzed in terms of coherence bandwidth.

The rest of this paper is organized as follows: in Section II, DFT-based channel estimation and its leakage problem are described. Section III reviews optimal and suboptimal linear estimators and analyzes the effect of coherence bandwidth on them. In Section IV, numerical results are presented to show the performance degradation due to the effect of coherence bandwidth. Conclusions are presented in Section V.

II. OFDM CHANNEL ESTIMATION

A. DFT-Based Channel Estimation

DFT-based interpolation is an efficient interpolation technique because of its good performance and low complexity [8, 9]. The PACE method using DFT-based interpolation is called DFT-based channel estimation, as shown in Fig. 2, where an inverse DFT (IDFT) operation is executed first to obtain the estimated channel impulse responses (CIRs) by using the LS-estimated CFRs at pilot subcarriers, and then, the estimated CIRs are transformed back into the frequency domain by the DFT operation to obtain the final CFRs at data subcarriers.

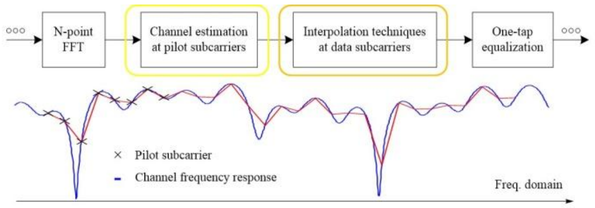

Fig. 1. Pilot-aided channel estimation for orthogonal frequency division multiplexing (OFDM) systems.

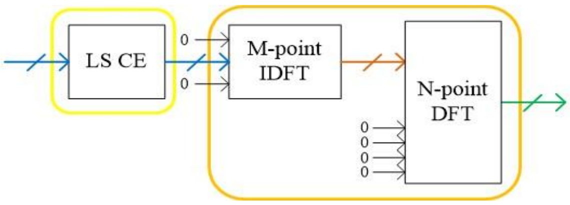

Fig. 2. Discrete Fourier transform (DFT)-based channel estimation. LS CE: least-squares channel estimation.

B. Virtual Carriers and Leakage Problem

In most commercialized OFDM systems, virtual carriers are exploited to ease the implementation of spectral masking filters and ensure guard bands to avoid interferences between adjacent systems [10].

However, these virtual carriers have a bad influence on the performance of DFT-based channel estimation. In other words, they may cause leakage effects. Virtual carriers correspond to rectangular windowing in the frequency domain, which results in the convolution of CIRs with the sinc function in the time domain. Hence, the channel taps of CIRs are leaked to one another. Further, time-domain windowing is performed to reduce the noise and interference, which causes spectral leakage or Gibbs phenomenon, as shown in Fig. 3.

In order to review the performance of DFT-based channel estimation and the leakage problem from virtual carriers, the normalized mean square error (NMSE) is represented as follows: Let the number of total subcarriers be $N = N_U + N_V + 1$, where $N_U + 1$ and N_V are the number of useful subcarriers and the number of virtual carriers, respectively. The number of cyclic prefix samples is defined as N_G. The received symbol at the *k*-th subcarrier is represented by

$$Y[k] = H[k]X[k] + W[k], -N_U/2 \le k \le N_U/2 \qquad (1)$$

where $X[k]$ is a transmitted symbol, $W[k]$ is a circularly symmetric complex Gaussian noise with zero mean and variance σ^2, and $H[k]$ is a CFR represented by

$$H[k] = \sum_{l=0}^{L-1} h[l] e^{-j2\pi kl/N}, \qquad (2)$$

where $h[l]$ is the *l*-th channel gain of an $L \times 1$ circularly symmetric complex Gaussian CIR vector $\mathbf{h}$ with zero mean and covariance matrix $\mathbf{C}_h = E[\mathbf{h}\mathbf{h}^H]$. The pilot symbols are assigned to estimate the CFR at pilot subcarriers

$$X[i_m] = P[m], 0 \le m \le N_P - 1, \qquad (3)$$

where $i_m = -N_U/2 + mD_f$ denotes a subcarrier location, D_f denotes the minimum pilot spacing, $P[m]$ denotes a

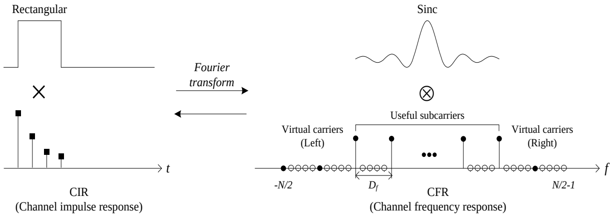

Fig. 3. Description of the reason for leakage effects.

pilot symbol with a binary phase shift keying constellation, and N_P denotes the number of pilot subcarriers.

The received pilot vector with entries $Y[i_m]$ is given by

$$\mathbf{Y} = \mathbf{X}\mathbf{H}_P + \mathbf{W} = \mathbf{X}\mathbf{F}\mathbf{h} + \mathbf{W}, \tag{4}$$

where $\mathbf{X}$ is a diagonal matrix with $P[m]$ on its diagonal, and $\mathbf{H}_P$ is a CFR vector, $\mathbf{W}$ is a noise vector with zero mean and covariance matrix $\sigma^2\mathbf{I}_P$ ($\mathbf{I}_P$ is an $N_P \times N_P$ identity matrix), and $\mathbf{F}$ is a DFT matrix with entries

$$[\mathbf{F}]_{m,n} = e^{-j2\pi i_m n/N}, \tag{5}$$

where $0 \le m \le N_P - 1$ and $0 \le n \le L - 1$. After the LS channel estimation at pilot subcarriers, the observation vector is represented by

$$\mathbf{Z} = \mathbf{X}^H\mathbf{Y} = \mathbf{X}^H\mathbf{X}\mathbf{F}\mathbf{h} + \mathbf{X}^H\mathbf{W} = \mathbf{F}\mathbf{h} + \breve{\mathbf{W}}, \tag{6}$$

where the noise vector $\breve{\mathbf{W}}$ is statistically equivalent to $\mathbf{W}$ since $E[\breve{\mathbf{W}}] = \mathbf{0}_{P\times 1}$ and $E[\breve{\mathbf{W}}\breve{\mathbf{W}}^H] = \sigma^2\mathbf{I}_P$. Here, $\mathbf{0}_{P\times 1}$ denotes an $N_P \times 1$ zero vector. The observation vector $\mathbf{Z}$ can be rewritten as $\tilde{\mathbf{Z}}$ to address the leakage effects

$$\begin{aligned}\tilde{\mathbf{Z}} &= \begin{bmatrix}\mathbf{0}_{b\times 1}\\ \mathbf{Z}\\ \mathbf{0}_{f\times 1}\end{bmatrix} = \begin{bmatrix}\mathbf{H}_{b\times 1}\\ \mathbf{F}\mathbf{h}\\ \mathbf{H}_{f\times 1}\end{bmatrix} + \begin{bmatrix}\mathbf{0}_{b\times 1}\\ \breve{\mathbf{W}}\\ \mathbf{0}_{f\times 1}\end{bmatrix} - \begin{bmatrix}\mathbf{H}_{b\times 1}\\ \mathbf{0}_{P\times 1}\\ \mathbf{H}_{f\times 1}\end{bmatrix}\\ &= \tilde{\mathbf{F}}\mathbf{h} + \tilde{\mathbf{W}} - \mathbf{H}_v,\end{aligned} \tag{7}$$

where $\tilde{\mathbf{Z}}$ is an $M \times 1$ observation vector, and $M = N_b + N_P + N_f$ is the number of pilot subcarriers including left-side virtual carriers (N_b) and right-side virtual carriers (N_f) with minimum pilot spacing. Here, $\mathbf{0}_{b\times 1}$ and $\mathbf{0}_{f\times 1}$ denote an $N_b \times 1$ zero vector and an $N_f \times 1$ zero vector, respectively. $\mathbf{H}_{b\times 1}$ and $\mathbf{H}_{f\times 1}$ denote an $N_b \times 1$ ideal CFR vector and an $N_f \times 1$ ideal CFR vector, respectively. In addition, $\tilde{\mathbf{F}}$ is a DFT matrix with entries

$$[\tilde{\mathbf{F}}]_{m,n} = e^{-j2\pi i'_m n/N}, \tag{8}$$

where $i'_m = -N_U/2 + (m - N_b)D_f$, $0 \le m \le M - 1$, and $0 \le n \le L - 1$. The IDFT operation transforms $\tilde{\mathbf{Z}}$ into the estimated CIR vector $\tilde{\mathbf{h}}$ in (9)

$$\tilde{\mathbf{h}} = (1/\mathrm{M}) \times \tilde{\mathbf{F}}^H\tilde{\mathbf{Z}}. \tag{9}$$

Then, the DFT operation transforms $\tilde{\mathbf{h}}$ into the estimated CFR vector $\tilde{\mathbf{H}}$ in (10)

$$\tilde{\mathbf{H}} = \mathbf{G}\tilde{\mathbf{h}} = \frac{1}{M}\mathbf{G}\tilde{\mathbf{F}}^H\tilde{\mathbf{Z}} = \mathbf{H} + \frac{1}{M}\mathbf{G}\tilde{\mathbf{F}}^H\tilde{\mathbf{W}} - \frac{1}{M}\mathbf{G}\tilde{\mathbf{F}}^H\mathbf{H}_v, \tag{10}$$

where $\tilde{\mathbf{F}}^H\tilde{\mathbf{F}} = M\mathbf{I}_L$, and $\mathbf{H} = \mathbf{G}\mathbf{h}$. Here, $\mathbf{G}$ is a DFT matrix with entries

$$[\mathbf{G}]_{m,n} = e^{-j2\pi mn/N}, \tag{11}$$

where $-N_U/2 \le m \le N_U/2$ and $0 \le n \le L - 1$. Note that the third term in (10) denotes the leakage. Now, the error covariance matrix of $\mathbf{H}$ can be given by

$$\mathbf{C} = \mathbf{E}\left[(\mathbf{H} - \tilde{\mathbf{H}})(\mathbf{H} - \tilde{\mathbf{H}})^H\right] = \frac{\sigma^2}{M^2}\mathbf{G}\mathbf{U}\mathbf{G}^H + \frac{1}{M^2}\mathbf{P}\mathbf{V}\mathbf{P}^H, \tag{12}$$

where $\mathbf{U} = \mathbf{F}^H\mathbf{F}$, $\mathbf{P} = \mathbf{G}\tilde{\mathbf{F}}^H$, and $\mathbf{V} = E[\mathbf{H}_v\mathbf{H}_v^H]$. To reveal the channel covariance matrix $\mathbf{C}_h$, $\mathbf{V}$ is rewritten as

$$\mathbf{V} = \mathbf{E}\left[(\tilde{\mathbf{F}}_v\mathbf{h})(\tilde{\mathbf{F}}_v\mathbf{h})^H\right] = \tilde{\mathbf{F}}_v\mathbf{C}_h\tilde{\mathbf{F}}_v^H, \tag{13}$$

where $\tilde{\mathbf{F}}_v$ denotes a DFT matrix with entries related to $\mathbf{H}_v$. The NMSE performance can be presented as

$$\begin{aligned}\varepsilon &= \frac{1}{N_U+1}tr(\mathbf{C})\\ &= \frac{1}{N_U+1}\frac{\sigma^2}{M^2}tr(\mathbf{G}\mathbf{U}\mathbf{G}^H) + \frac{1}{N_U+1}\frac{1}{M^2}tr(\mathbf{P}\mathbf{V}\mathbf{P}^H).\end{aligned} \tag{14}$$

where the first term denotes the noise effects and the second term denotes the leakage effects.

III. EFFECT OF COHERENCE BANDWIDTH ON LEAKAGE SUPPRESSION METHODS

A. Review of Leakage Suppression Methods

In order to minimize the NMSE in (14), optimal and sub-optimal linear estimators were proposed in [11]. They can be expressed as

$$\mathbf{K}_{opt} = \tilde{\mathbf{F}}_v\mathbf{C}_h\mathbf{F}^H(\mathbf{F}\mathbf{C}_h\mathbf{F}^H + \sigma^2\mathbf{I}_P)^{-1}, \tag{15}$$

$$\mathbf{K}_{sub} = \frac{1}{L}\tilde{\mathbf{F}}_v\mathbf{F}^H\left(\frac{1}{L}\mathbf{F}\mathbf{F}^H + \sigma^2\mathbf{I}_P\right)^{-1}. \tag{16}$$

Then, optimal or suboptimal linear estimators are used to estimate $\hat{\mathbf{H}}_v = \mathbf{K}_{opt}\mathbf{Z}$ or $\hat{\mathbf{H}}_v = \mathbf{K}_{sub}\mathbf{Z}$, respectively. Their error covariance matrices can be given by

$$\mathbf{C}_{opt} = \frac{\sigma^2}{M^2}\mathbf{G}\mathbf{U}\mathbf{G}^H + \frac{1}{M^2}\mathbf{P}\mathbf{V}_{opt}\mathbf{P}^H, \tag{17}$$

$$\mathbf{C}_{sub} = \frac{\sigma^2}{M^2}\mathbf{G}\mathbf{U}\mathbf{G}^H + \frac{1}{M^2}\mathbf{P}\mathbf{V}_{sub}\mathbf{P}^H, \tag{18}$$

where $\mathbf{V}_{opt}$ and $\mathbf{V}_{sub}$ are represented as

$$\mathbf{V}_{opt} = E\left[(\mathbf{H}_v - \mathbf{K}_{opt}\mathbf{Z})(\mathbf{H}_v - \mathbf{K}_{opt}\mathbf{Z})^H\right], \tag{19}$$

$$\mathbf{V}_{sub} = E[(\mathbf{H}_v - \mathbf{K}_{sub}\mathbf{Z})(\mathbf{H}_v - \mathbf{K}_{sub}\mathbf{Z})^H]. \tag{20}$$

Finally, their NMSEs are given by

$$\varepsilon_{opt} = \frac{1}{N_U+1}\frac{\sigma^2}{M^2}tr(\mathbf{GUG}^H) + \frac{1}{N_U+1}\frac{1}{M^2}tr\left(\mathbf{PV}_{opt}\mathbf{P}^H\right), \quad (21)$$

$$\varepsilon_{sub} = \frac{1}{N_U+1}\frac{\sigma^2}{M^2}tr(\mathbf{GUG}^H) + \frac{1}{N_U+1}\frac{1}{M^2}tr\left(\mathbf{PV}_{sub}\mathbf{P}^H\right). \quad (22)$$

From (21) and (22), we find that the NMSE performance improvement depends on the second terms $\mathbf{V}_{opt}$ and $\mathbf{V}_{sub}$, respectively.

B. Effect of Coherence Bandwidth

Although optimal and suboptimal linear estimators provide good performance with moderate complexity, their performance may decrease according to wireless channel conditions such as coherence bandwidth.

Coherence bandwidth is a statistical measurement of the range of frequencies over which the channel can be considered flat [12]. The coherence bandwidth can be approximately defined as

$$B_c \approx \frac{1}{\tau_{max}} = \frac{1}{LT_s}. \quad (23)$$

where τ_{max} is the maximum delay spread of a wireless channel and T_s is the sampling time of an OFDM system. If the coherence bandwidth is divided by the subcarrier spacing $\Delta f = 1/NT_s$, the number of subcarriers in the range of the coherence bandwidth can be obtained. For instance,

$$\frac{B_c}{\Delta f} = \frac{N}{L} = \frac{512}{20} \approx 25, \quad (24)$$

where we assume N = 512 and L = 20. If the minimum pilot spacing is D_f = 8, three D_f-spaced virtual carriers will be in the range of the coherence bandwidth, as shown in Fig. 4.

Therefore, if optimal and suboptimal linear estimators try to estimate CFRs outside the range of the coherence bandwidth, they may experience a decrease in their performance.

IV. NUMERICAL RESULTS

Computer simulations have been run to analyze leakage suppression methods such as optimal and suboptimal linear estimators in terms of the coherence bandwidth of wireless channels. We consider the OFDM system using QPSK modulation in the 1.25-MHz bandwidth at 2.3 GHz with $N_G = 32$, $N = 512$, $N_U + 1 = 481$, $N_V = 31$, $D_f = 8$, $N_P = 61$, and $M = 64$. The multipath fading channel is assumed to have an exponential power delay profile with $L = 20$.

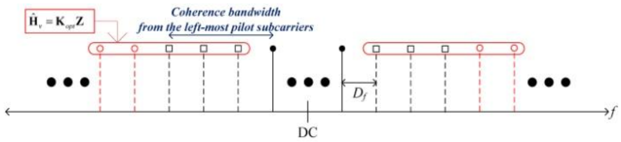

Fig. 4. Coherence bandwidth and minimum pilot spacing.

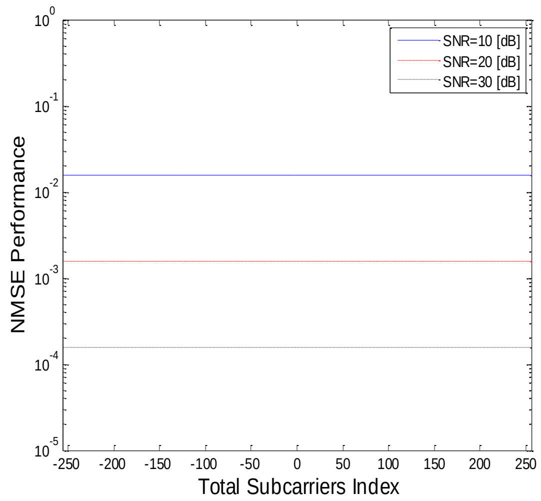

Fig. 5. Normalized mean square error (NMSE) performance in case of no virtual carriers. SNR: signal-to-noise ratio.

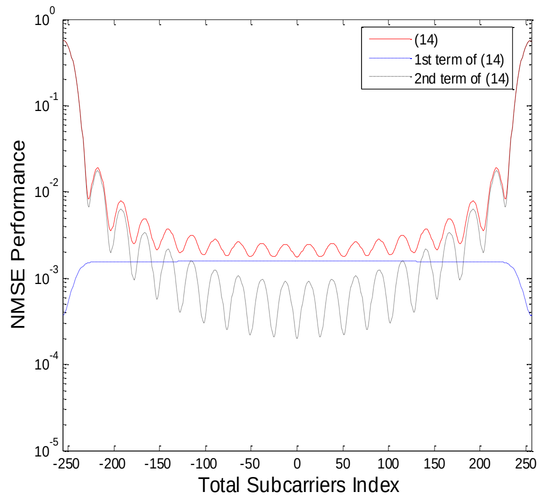

Fig. 6. Normalized mean square error (NMSE) performance of the conventional method (signal-to-noise ratio [SNR] = 20 dB).

Fig. 5 shows the NMSE performance of DFT-based channel estimation in the case of no virtual carriers. It has constant values determined by the noise variance or the signal-to-noise power ratio (SNR). In contrast, Fig. 6 shows the NMSE performance in the case of virtual carriers (namely, conventional DFT-based channel estimators), which is theoretically plotted according to the total subcarriers index by using (14). The first term in (14) strongly depends on the

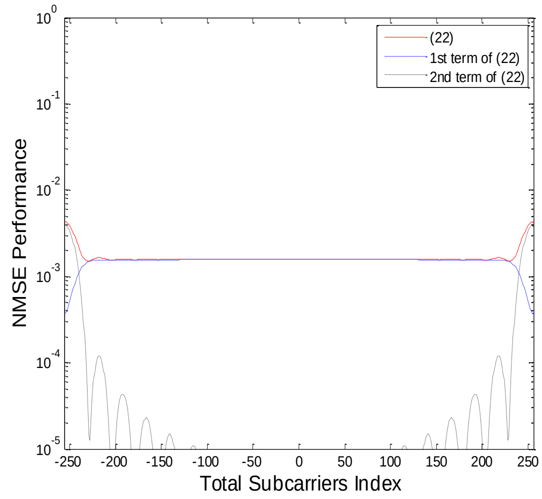

Fig. 7. Normalized mean square error (NMSE) performance of the sub-optimal method (signal-to-noise ratio [SNR] = 20 dB).

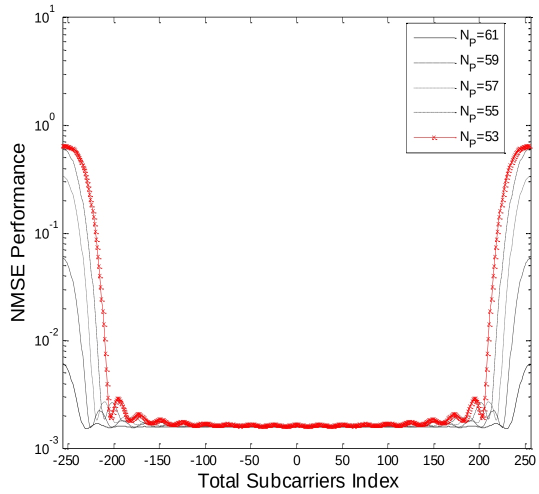

Fig. 9. Normalized mean square error (NMSE) performance of the sub-optimal method ($\sigma^2 = 10$).

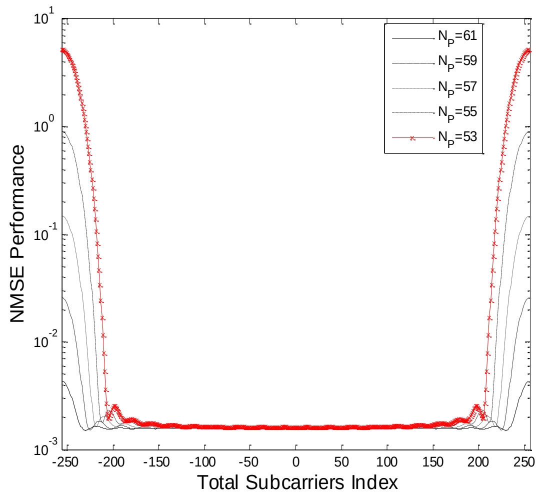

Fig. 8. Normalized mean square error (NMSE) performance of the sub-optimal method ($\sigma^2 = 40$).

noise variance, whereas the second term leads to the leakage. In addition, the second term is the dominant factor in performance degradation, particularly at edge subcarriers.

Fig. 7 shows the performance improvement resulting from the suboptimal linear estimator by using $\sigma^2 = 40$ in (16). The first term is the same as that in Fig. 6, but the second term is highly improved when compared with that in Fig. 6.

Fig. 8 illustrates the NMSE performance of the sub-optimal linear estimator with $\sigma^2 = 40$ in (16) as the number of pilot subcarriers (N_P) decreases, which means that the number of D_f-spaced virtual carriers to be estimated increases. Further, Fig. 9 illustrates the NMSE performance of the suboptimal linear estimator with $\sigma^2 = 10$. By comparing Fig. 8 with Fig. 9 when $N_P = 61, 59, 57$, we find that the suboptimal linear estimator with $\sigma^2 = 40$ is superior to that with $\sigma^2 = 10$. Due to the high SNR assumption in [13], these results are reasonable. However, when $N_P = 55, 53$, the NMSE performances in Fig. 8 are more severely degraded.

These results denote the cases in which the D_f-spaced virtual carriers to be estimated are out of the range of the coherence bandwidth. In other words, the D_f-spaced virtual carriers outside the coherence bandwidth are sensitive to the SNR mismatch. In addition, the SNR mismatch of the suboptimal linear estimator with $\sigma^2 = 40$ is more critical than that of the suboptimal linear estimator with $\sigma^2 = 10$, when the actual SNR is 20 dB. Hence, the channel estimation errors outside the coherence bandwidth resulting from the SNR mismatch cause the entire performance degradation.

V. CONCLUSIONS

In this study, the effect of the coherence bandwidth of wireless channels on leakage suppression methods such as the optimal and suboptimal linear estimators for OFDM channel estimation was analyzed. The NMSE performances of these methods were very sensitive to the coherence bandwidth of wireless channels. If some of the estimated CFRs were placed out of the range of the coherence band-width, a severe channel estimation error occurred at edge subcarriers and the entire NMSE performance decreased. Further, the SNR mismatch of the suboptimal linear estimators was more critical in these cases.

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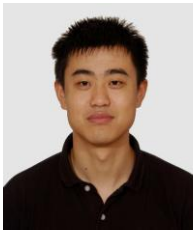

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