Semi-blind Channel Estimation on 802.11 OFDM Data Symbols

Christopher J. Hansen
Covariant Corporation
Los Altos, CA, USA
chris@covariantcorp.com

***Abstract*—New wireless local area network designs are placing a greater emphasis on reliability, which motivates a reexamination of physical layer protocols. It also motivates techniques to improve the reliability of legacy protocols, since legacy protocols are often used alongside new protocols. This paper introduces a technique for receiving legacy IEEE 802.11 packets when the PHY header is corrupted or unavailable by performing a blind or semi-blind channel estimation using unknown data symbols. The technique can improve reliability by allowing reception of packets that would otherwise be discarded. It also suggests additional features that could be added to future wireless local area network standards to improve reliability.**

***Index Terms*—Wireless LAN (wlan), 802.11, channel estimation, blind estimation, least squares, total least squares**

I. Introduction

Recent work in the IEEE 802.11 standards body has been examining ultra-high reliability networks [1]. This is a departure from past efforts that have been devoted to higher throughput rates or higher efficiency. Although ultra-high reliability has not yet been precisely defined in IEEE standards, it is generally understood that reduction in packet latency is an important, if not the most important goal. Since latency is exacerbated when packets are not successfully received, it is beneficial to look at methods for enhanced reception. For 802.11, this is especially true since legacy packet formats, such as those from 802.11a, are commonly used for key functions and will continue to be used in the future. Thus, improvements to overall reliability require improvements for reception of legacy formats.

IEEE 802.11 employs packets, or physical layer protocol data units (PPDUs), that include a preamble [2]. The preamble is used by the receiving station for initial synchronization, determination of the packet format, and channel estimation. The simplest PPDU format is the one defined in Clause 17, which was originally part of IEEE 802.11a-1999, and is shown in Fig. 1. The PHY preamble (STF and LTF blocks) and PHY header (SIG block) together are $20\mu s$ long. Over time, the preambles for 802.11 PPDUs have grown in length and complexity but their function remains the same. An example from IEEE 802.11ax [3] is shown in Fig. 2. Here the PHY preamble (which includes the signaling of the legacy 802.11a PHY Header) is over $40\mu s$ long.

Long preambles are a source of both inefficiency and increased susceptibility to packet errors. Inefficiency is due to the fact that time used to transmit preambles is time that

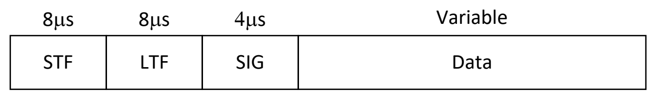

Fig. 1. Legacy PPDU Format from IEEE 802.11a

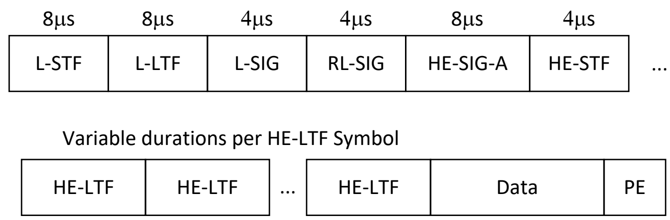

Fig. 2. PPDU Format from IEEE 802.11ax

is not used to transmit data. Longer preambles are also more complex to process, and any error in processing the preamble will usually cause the entire packet to be lost. The IEEE 802.11 standard has addressed the inefficiency issue by allowing each new PPDU format to carry more data. Thus, the relative fraction of transmission time dedicated to the preamble is reduced. Longer 802.11 PPDUs are also robust, since they are typically broken into segments, called A-MPDU (Aggregated-MAC Protocol Data Units) subframes, that are acknowledged independently. An error or burst of errors in one segment can be contained to that segment. The other segments in the PPDU are not lost.

Improving the reliability of the preamble is more complicated and requires new approaches. This work presents a technique for channel estimation on data symbols that can allow reliance on the preamble to be reduced and, in some cases, eliminated.

II. Background

New channel estimation techniques that are appropriate for processing 802.11 preamble training symbols have been published recently. For example, [4] and [5] show that it is possible to improve channel estimates by also estimating the channel length, thus allowing the receiver to compute an estimate that matches the actual channel length and minimizes

979-8-3503-7099-7/24/$31.00 ©2024 IEEE

the impact of noise. These techniques are also helpful for improving reliability, since any degradation due to errors in channel estimates (e.g. in receiver equalization or transmit beam-forming) will be reduced as the channel estimates are improved. These techniques are most useful when the packet preamble is impaired by a level of noise that is comparable to the noise on the received data symbols. While they can be applied to legacy 802.11 packet formats, they are not suitable for the case when a packet preamble is severely impaired or lost due to a collision.

The approach in this work is designed for situations when the packet preamble is lost. It begins with multichannel blind identification, which has received considerable attention in the past [6]. Multichannel techniques, which can be implemented with oversampling, are suitable for modern IEEE 802.11 implementations, especially when receiving legacy PPDUs such as beacons. These PPDUs typically employ a 20 MHz bandwidth, which is narrower than the 80 to 320 MHz bandwidth that is often used for data PPDUs.

Blind identification techniques can be classified into statistical and deterministic methods. Deterministic methods are generally simpler to employ in a practical environment because knowledge of signal statistics, which could involve long measurements, is not necessary. This work employs a deterministic method based on the least squares approach to blind channel estimation described in [7] and [8].

Alternative approaches that employ statistical methods for blind identification of IEEE 802.11 channels have recently been explored in [9] and [10]. Like those works, this work exploits pilot subcarriers for an absolute phase reference in the channel estimate. However, the use of least squares in this work allows the pilots to also provide additional constraints to improve the channel estimate. Furthermore, this work only requires a small number of OFDM symbols, typically one or two, which is far fewer than what is required with the statistical methods.

Related work has explored the use of deep learning to semi-blind estimation of OFDM channels [11]. This technique holds great promise, but would require changes to pilot placement in the IEEE 802.11 standard to be applied in practice. This work, in contrast, supports existing protocols including their use of pilots. These existing protocols are used throughout the world and are likely to be in place for the foreseeable future.

III. System Model

It is assumed the receiver employs oversampling to produce multiple FIR channel responses $h_i(n)$. Oversampling is common in implementations of IEEE 802.11 receivers. For 802.11 PPDU types employing Orthogonal Frequency Division Multiplexing (OFDM), the receiver will observe the sequence of OFDM data symbols $s(k)$ through these channels as:

$$x_i(k) = \sum_{j=0}^{L} h_i(j)s(k-j)+n_i(k) = h_i(k)*s(k)+n_i(k) \quad (1)$$

where i is the observed channel, j is the index of the channel impulse response on the observed channel, k is the received sample index, and $n_i(k)$ is additive white Gaussian noise (AWGN) on channel i that is observed on sample k. Assuming the noise is negligible we can follow [7] and note that for any pair of channel impulse responses $i \neq j$:

$$x_i(k) * h_j(k) = x_j(k) * h_i(k) = h_i(k) * h_j(k) * s(k) \quad (2)$$

Each OFDM symbol includes a cyclic prefix to avoid inter-symbol interference (ISI) from the previous symbol. The cyclic prefix has the effect of converting the linear convolutions of (2) into cyclic convolutions when the channel response is shorter than the cyclic prefix. The cyclic convolution of the length N OFDM symbol with the length M channel can be expressed with a matrix multiplication:

$$x_i(k) \circledast h_j(k) = X_i h_j = \begin{bmatrix} x_i(1) & x_i(N) & \dots & x_i(N-M+2) \\ x_i(2) & x_i(1) & \dots & x_i(N-M+3) \\ \vdots & \vdots & \dots & \vdots \\ x_i(N) & x_i(N-1) & \dots & x_i(N-M+1) \end{bmatrix} \begin{bmatrix} h_j(1) \\ h_j(2) \\ \vdots \\ h_j(M) \end{bmatrix} \quad (3)$$

Solutions for a pair of channel estimates can be determined from:

$$\begin{bmatrix} X_i & -X_j \end{bmatrix} \begin{bmatrix} \hat{h}_j \\ \hat{h}_i \end{bmatrix} = 0. \quad (4)$$

In practice, however, a solution to (4) is not sufficient since it does not provide an absolute amplitude and phase reference for the channel, which is required by the receiver for equalization. It is possible to resolve this, and reduce the error in the estimate, by adding constraints for known pilot signals within the OFDM data symbol.

IV. Optimizing the Model for 802.11 Symbols

All IEEE 802.11 OFDM data symbols contain pilot subcarriers to allow for carrier phase tracking in the receiver. For example, in the legacy 802.11a PPDU format, sometimes referred to as non-HT in the standard, OFDM data symbols employ a 64 point discrete Fourier transform (DFT) with pilots on subcarriers $k \in \{-21, -7, 7, 21\}$. The received pilot over channel h_i for subcarrier k on symbol n will be:

$$r_{i,k,n} = d_{k,n} W_{k,1..M} h_i. \quad (5)$$

where $d_{k,n}$ is the value of the pilot sequence and $W_{k,1..M}$ are the first M elements of the row of the DFT matrix, W corresponding to the pilot subcarrier k. Since 802.11 pilots are modulated using BPSK with a known sequence, (5) can be rewritten for all pilots in the symbol:

$$W_p h_i = b_{i,n} \quad (6)$$

where

$$W_p = \begin{bmatrix} W_{-21,1..M} \\ W_{-7,1..M} \\ W_{7,1..M} \\ W_{21,1..M} \end{bmatrix} \tag{7}$$

and

$$b_{i,n} = \begin{bmatrix} d_{-21,n} r_{i,-21,n} \\ d_{-7,n} r_{i,-7,n} \\ d_{7,n} r_{i,7,n} \\ d_{21,n} r_{i,21,n} \end{bmatrix} \tag{8}$$

Combining the blind estimation constraint (4) and the pilot estimation constraint (5) together yields:

$$\begin{bmatrix} X_{i,n} & -X_{j,n} \\ W_p & W_p \end{bmatrix} \begin{bmatrix} \hat{h}_j \\ \hat{h}_i \end{bmatrix} = \begin{bmatrix} 0 \\ b_{j,n} \\ b_{i,n} \end{bmatrix} \tag{9}$$

which is sufficient for determining the channel estimates from any data symbol n. In addition, it is easy to extend (9) to multiple 802.11 OFDM symbols by adding rows for each symbol.

V. Results

The solution to (9) can be found by found by direct application of the normal equations [12], but a significant reduction in the error is possible by applying the principles of Weighted Least Squares and Total Least Squares. For Weighted Least Squares, a row weighting (> 1) is applied to the pilot portion relative to blind estimate portion, enhancing the the impact of each pilot constraint to the solution. Re-writing (9) with the weight δ_p gives:

$$A = \begin{bmatrix} X_{i,n} & -X_{j,n} \\ \delta_p W_p & \delta_p W_p \end{bmatrix} \tag{10}$$

$$\hat{h} = \begin{bmatrix} \hat{h}_j \\ \hat{h}_i \end{bmatrix} \tag{11}$$

and

$$b = \delta_p \begin{bmatrix} 0 \\ b_{j,n} \\ b_{i,n} \end{bmatrix} \tag{12}$$

with

$$A\hat{h} = b. \tag{13}$$

The weight that minimizes the estimation error will depend on the particular channel and the received signal-to-noise ratio (SNR). An example is shown of the CCDF (complementary cumulative distribution function) of the estimation errors in Fig. 3. Here, the weighted semi-blind channel estimates are computed with the normal equations:

$$\hat{h} = (A^H A)^{-1} A^H b \tag{14}$$

using δ_p values of 1,8, and 16.

A set of IEEE 802.11 type complex passband FIR channels was generated in Matlab using the WLAN System Toolbox. Each channel was 20 MHz wide and sampled at 40 MHz, yielding a pair of channels suitable for semi-blind estimation. An IEEE 802.11 non-HT type PPDU was convolved with each channel from a pair. Noise was added such that the received SNR for each PPDU was 15 dB. For reference, a channel estimate was made from the LTF (long training field) of the PPDU preamble by first removing the cyclic prefix, averaging over the FFT of each long training symbol, and then multiplying each tone by the values in (17-8) of [2] to remove the LTF modulation. The reference is typical of channel estimation used in current IEEE 802.11 implementations.

The solid line shows the CCDF of the reference estimate using the PPDU preamble information in the LTF. The dashed curves show error CCDFs for the semi-blind channel estimation with different weights using 2 OFDM data symbols. Two symbols were used for comparison, since they occupy the same time on the air as the LTF in the preamble.

A weight value greater than 1 reduces the estimation error with a value of roughly 8 yielding a minimum. With this value, the median error is the same as the LTF reference. With weights greater than 8, the error starts to increase.

The normal equation approach finds $\hat{h}$ such that:

$$\min_{\hat{h} \in \mathbb{C}^n} ||A\hat{h} - b||_2 \tag{15}$$

which is optimal when the matrix A is known exactly. When the number of rows of A exceeds the number of elements in b, errors due to noise in b are reduced. This is true for channel estimation with a known sequence. However, for semi-blind channel estimation, the sub-matrices $X_{i,n}$ and $X_{j,n}$ are also received signals that are impaired with noise.

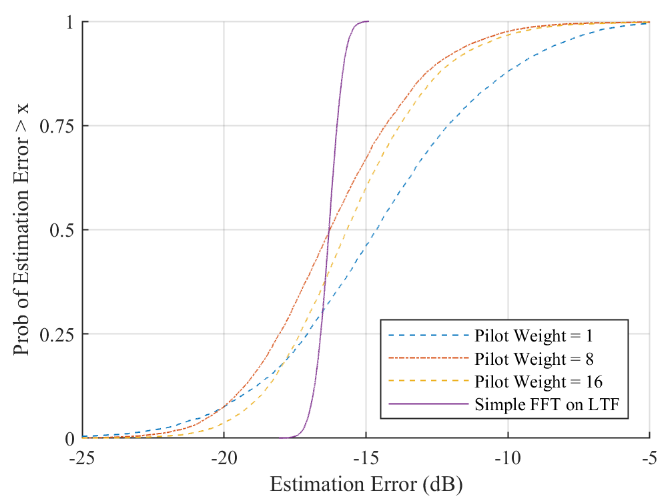

Fig. 3. Semi-blind Estimation with Normal Equations

A significant reduction in the estimation error can be made by solving (13) using the method of total least squares (TLS) [13].

TLS works by first solving:

$$\min_{[\hat{A}\ \hat{b}]} ||[A\ b] - [\hat{A}\ \hat{b}]||_2 \tag{16}$$

with $\hat{b}$ in the range of $\hat{A}$ and $\hat{h}$ a solution of:

$$\hat{A}\hat{h} = \hat{b} \tag{17}$$

which has the effect of removing a component of the error in both A and b.

In practice, the TLS solution is found by modifying (13):

$$[A\ b] \begin{bmatrix} \hat{h} \\ -1 \end{bmatrix} \approx 0 \tag{18}$$

and compute the singular value decomposition:

$$U \Sigma V^H = [A\ b] \tag{19}$$

where U and V are orthonormal matrices and Σ is a diagonal matrix:

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & 0 & \dots & 0 \\ 0 & \sigma_2 & 0 & \dots & 0 \\ 0 & 0 & \ddots & & \\ 0 & 0 & \dots & \sigma_n & 0 \\ 0 & 0 & 0 & \dots & \epsilon \end{bmatrix} \tag{20}$$

The singular values are ranked:

$$\sigma_1 > \sigma_2 > \dots > \sigma_n \gg \epsilon \tag{21}$$

with the smallest being close to zero.

The TLS solution for $\hat{h}$ is then found from scaling the first n elements of the right most column of V by the last element of that column:

$$\hat{h} = \frac{-1}{V_{n+1,n+1}} V_{1..n,n+1} \tag{22}$$

Fig. 4 is a CCDF plot of the solution using TLS with weights 1, 2, and 4 for the known pilots. The best choice of weighting is 2 and this produces an error that is roughly 3 dB better than the solution to the normal equations. Note also that with TLS, the error is less than the reference estimate for 80 percent of the channels.

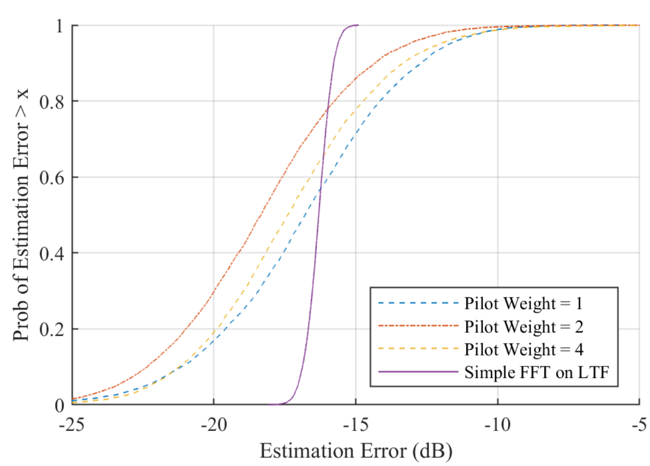

Fig. 4. Semi-blind Estimation with Total Least Squares

VI. 802.11 Beacon Frame Example

A practical test of the semi-blind channel estimation technique employed on an actual IEEE 802.11 beacon frame was carried out. In IEEE 802.11, beacon frames are transmitted by access points (AP) to signal their presence to other stations, typically clients, and to provide information necessary for association [2]. The beacon frame was selected as an example because it uses the legacy 802.11a-1999 PHY protocol and is ubiquitous. Improving the reliability of beacon detection can allow faster initial access or hand-off to a wireless network.

In normal practice, beacons in the 5 GHz band are transmitted at the 6 Mbps rate, which employs BPSK modulation on the OFDM sub-carriers. Thus, to demodulate and decode a beacon, it is not necessary to know the contents of the PPDU preamble. It is only necessary to synchronize and perform channel estimation. In this example, the synchronization is assumed to have already been performed. The semi-blind channel estimation is performed on the first two received OFDM data symbols to determine the channel estimate. The channel estimate is then used to equalize the received data symbols.

A beacon frame was captured off the air at 5.475 GHz from an off-the-shelf 802.11 AP using an Analog Devices ADRV9361-Z7035 SDR 2x2 System-On-Module and Matlab. The channel bandwidth was 20 MHz and the sampling rate was 40 Msamples/s. An example captured Beacon frame is shown in Fig. 5. Only the first 28 μs are shown. An 802.11 receiver will use L-LTF symbols (i.e., from 8 - 16 μs), for channel estimation. In this example, the first two data symbols (i.e., 20 - 28 μs) are used for semi-blind channel estimation.

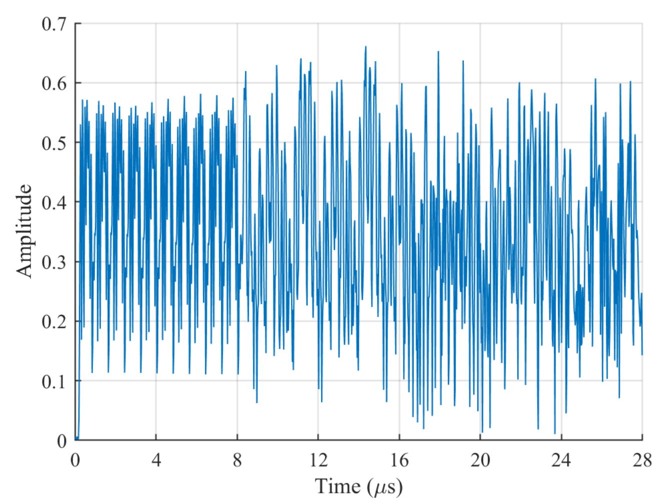

Fig. 5. 802.11 Beacon

Fig. 6 shows the taps amplitudes from the pair of channel estimates computed using the TLS method of (22). The estimates were then input to the Matlab WLAN Toolbox for demodulation and decoding. Fig. 7 shows the received constellation points obtained when using the first channel. The received beacon was verified to be received correctly via a valid FCS (frame check sequence) and a match to the MAC address of AP.

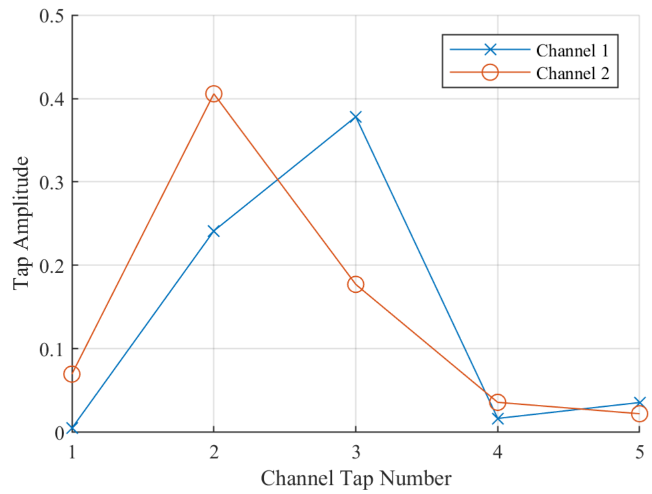

Fig. 6. Channel Estimate Taps

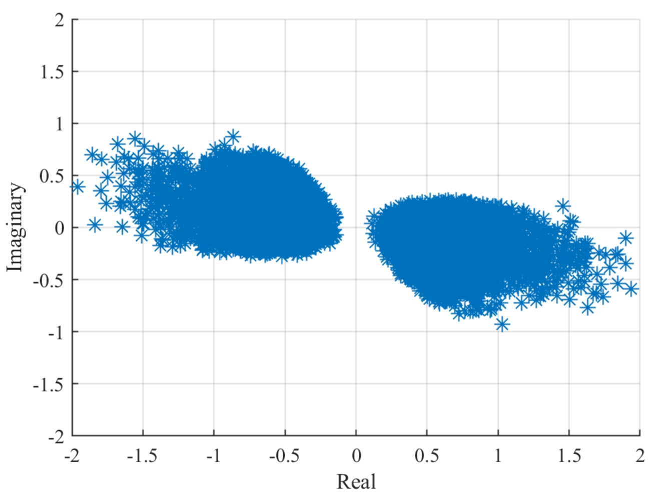

Fig. 7. Received Constellation Points

VII. Conclusions

This work has demonstrated the practicality of using semi-blind channel estimation with least squares for the reception of legacy IEEE 802.11 packets. This technique leverages existing pilot tones in OFDM data symbols. The pilot tones themselves are insufficient for channel estimation, but can be used to enhance a blind channel estimate. This estimate can then be used to demodulate frames, such as legacy beacon frames, even when the PHY preamble is not available.

Extending the semi-blind technique to other PPDU formats, such as those with MIMO, may also be possible. Future wireless standards, such as those seeking ultra-high reliability, may also provide structures to enhance semi-blind techniques. This is an area of future research.

References

[1] E. Park, et al., *Potential PHY Features for UHR*, [Online] Available: https://mentor.ieee.org/802.11/dcn/22/11-22-1466-00-0uhr-potential-phy-features-for-uhr.pptx

[2] *IEEE Standard for Information Technology— Telecommunications and Information Exchange between Systems Local and Metropolitan Area Networks— Specific Requirements Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications*, IEEE Std. 802.11-2020.

[3] *IEEE Standard for Information Technology— Telecommunications and Information Exchange between Systems Local and Metropolitan Area Networks— Specific Requirements Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications Amendment 1: Enhancements for High-Efficiency WLAN*, IEEE Std. 802.11ax-2021.

[4] H. Park. "Adaptive Channel Estimate for OFDM Systems Using CIR Length Estimate," *IEEE Wireless Communications Letters*, Vol. 10, No. 11, pp. 2597–2601.

[5] A. Tomasoni, D. Gatti, S. Bellini, M. Ferrari, and M. Siti. "Efficient OFDM Channel Estimation via an Information Criterion," *IEEE Trans. on Wireless Communications*, vol. 12, no. 3, pp. 1352–1363, 2013.

[6] L. Tong and S. Perreau. "Multichannel Blind Identification: From Subspace to Maximum Likelihood Methods." *Proc. of the IEEE*, vol. 86, No. 10, pp. 1951–1968.

[7] G. Xu, H. Liu, L. Tong, and T. Kailath. "A Least-Squares Approch to Blind Channel Identification," *IEEE Trans. on Signal Processing*, vol. 43, no. 12, pp. 2982–2993, 1995.

[8] H. Wang, Y. Lin, and B. Chen. "Data-Efficient Blind OFDM Channel Estimation Using Receiver Diversity," *IEEE Trans. on Signal Processing*, vol. 51, no. 10, pp. 2613–2623, 2003.

[9] M. Awad, K. Seddik, and A. Elezabi. "Low-Complexity Semi-Blind Channel Estimation Algorithms for Vehicular Communications Using the IEEE 802.11p Standard," *IEEE Trans. on Intelligent Transportation Systems*, vol. 20, no. 5, pp. 1739–1748.

[10] A. Ladaycia, M. Pesavento, A. Mokraoui, K. Abed-Merain, and A. Belouchrani. "Decision Feedback Semi-Blind Estimation Algorithm for Specular OFDM Channels" *2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp.4664–4668.

[11] C. Liu and T. Arslan. "RecNet: Deep Learning-Based OFDM Receiver with Semi-Blind Channel Estimation," *2020 IEEE International Symposium on Circuits and Systems (ISCAS).*

[12] *Matrix Computations, 4th Ed.* G. Golub and C. Van Loan, Baltimore, MD, USA: Johns-Hopkins University Press, 2013.

[13] *The Total Least Squares Problem: Computational Aspects and Analysis* S. Van Huffel and J. Vandewall, Philadelphia, PA, USA: SIAM, 1991.