Abstract—The vehicle-to-vehicle (V2V) communications channel is highly time-varying, making reliable communication difficult. This problem is particularly challenging because the de facto standard for V2V communications, the IEEE 802.11p standard, is based on the IEEE 802.11a standard, which was designed for the indoor and relatively stationary wireless LAN channel. In particular, the frame structure which allows large packets and has low pilot density makes channel estimation difficult. In this paper, we propose several semi-blind channel estimation and tracking algorithms that are suitable for highly time-varying channels using the 802.11p frame structure. Two of the proposed schemes utilize the finite alphabet property of the transmitted symbols and utilize pilot information. A third scheme is a variant of decision-directed channel estimation that utilizes knowledge of the preamble. All schemes apply time-domain channel impulse response truncation for improved performance. We compare the performance of the proposed schemes using six different V2V channel models. The proposed schemes realize huge performance gains over previously proposed ones, reaching 20 dB in some cases, where previously proposed schemes are unusable. These performance gains are realized for all the V2V channel models, at different vehicle velocities, and for all modulation schemes and packet sizes. Two of the proposed schemes are low-complexity schemes that avoid expensive search operations, yet offer significantly improved performance.

I. INTRODUCTION

Vehicular communications are an essential and integral component of intelligent transportation systems (ITSs) including the concept of the connected vehicle that is heralded as the new revolution in the automobile industry [1], [2]. ITSs with their many facets in turn are among the main hallmarks of futuristic smart cities [3]. Autonomous vehicles [4] promise to radically transform the driving experience, and human mobility in general. Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications are the main enabling technologies for such ITS applications. Examples of the need for such vehicular communications include cooperative driving for merging, platooning, and lane keeping [5]–[7]. Among other things, those innovations promise to improve road safety as drivers would get safety messages and alerts of expected road hazards. Moreover, vehicular communication can reduce traffic jams and decrease road accidents via various applications such as traffic light optimal speed advisory, cooperative forward collision warning, hazardous location V2V notifications, and remote wireless vehicle diagnosis [1], [8]. To realize such myriad applications, a robust network of connected vehicles is needed where neighboring vehicles are connected to one another and to the infrastructure.

In order to realize such vehicular connectivity, accurate and reliable channel estimation is essential. In vehicular communication systems, in particular, there are many challenges to accurate channel estimation and hence reliable communications, such as the highly time-varying channel characteristics due to high vehicular speeds, the high mobility of the environment including transmitter, receiver, and scatterers, large variance in angle of arrivals, deep fades due to clutter, and shadowing due to buildings.

The IEEE 802.11p standard, commonly referred to as Dedicated Short Range Communication (DSRC), is the de facto industry-adopted standard for V2V communications. DSRC is one of the fundamental building blocks of the US Department of Transportation vehicle infrastructure integration (VII) initiative [9], where a nationwide system is envisioned in which vehicles communicate with each other and the transportation infrastructure. The purpose is to provide new services that ensure road safety, reduce highway fatalities, provide mobility and commercial benefits to improve the quality of life [10].

IEEE 802.11p is a variant of the well-known standard IEEE 802.11a with very few changes such as channel bandwidth and frequency bands. Specifically, the IEEE 802.11a has a 20 MHz bandwidth, while IEEE 802.11p has a 10 MHz bandwidth, and the IEEE 802.11p operates in the 5.9 GHz frequency bands whereas IEEE 802.11a operates most commonly in the 2.4 GHz. Because IEEE 802.11a was developed for relatively stationary environments applicable for indoor use, IEEE 802.11a receivers initially estimate the channel response based on a known preamble in the packet header. The channel response is assumed to be relatively static for the entire packet duration and the entire packet is therefore equalized based on the initial channel estimate. On the other hand, V2V communications have a small coherence time due to the fact that the transmitter, receiver and the scatterers are all in motion and the channel varies greatly over the packet duration. Hence, channel estimation for V2V communications is a very challenging problem. Addressing this challenge within the confines of the IEEE 802.11p standard is the aim of this paper.

A lot of the work done on channel estimation algorithms for OFDM systems in highly dynamic environments is independent of any specific standard [11], [12]; while some work has been done on the channel estimation and tracking for the IEEE 802.11p standard. The reported performance in such works is still inadequate, however, to realize V2V applications based on IEEE 802.11p. For example, the performance study in [13]
indicated that conventional least squares channel estimation, which uses the channel estimate obtained from the packet preamble, is not a suitable choice for V2V applications. In order to obtain adequate performance in V2V systems, it is necessary to better track the rapid fluctuation of the channel response within the packet duration.

In [14], several channel estimation schemes were developed where it was shown that the Packet Error Rate (PER) could be improved using spectral temporal averaging (STA) instead of the conventional least squares estimator (LS). However, this scheme requires perfect knowledge of the radio environment to compute the algorithm parameters and their updates, which is hard to achieve in practice. Therefore, fixed average channel parameters were used with no adaptation, resulting in degraded system performance. In [10], a decision-directed equalization scheme was described that improves the PER for V2V communication. A hardware implementation of this scheme was described to illustrate its implementation feasibility. This improved equalization was extended to all of the data rates available in the standard. However, in addition to the high complexity of decision-directed schemes in general, the delay in this scheme was also large, as the feedback from the Viterbi decoder propagates through the entire back end chain before a channel estimate is calculated. In [15], an advanced receiver scheme was proposed that also uses decision-directed channel estimation that is complemented with channel smoothing to enhance performance. This was achieved at the expense of a large increase in computational complexity due to multiplication of large matrices. In the same paper, complexity reduction techniques were proposed, but resulted in unacceptable performance degradation. A survey on IEEE 802.11p channel estimation and tracking algorithms is presented in [16], as well as a novel channel estimation algorithm that outperforms some previously proposed schemes by making use of decision-directed estimation and channel correlation between successive symbols to calculate the channel estimates.

In this paper, we propose three different channel estimation and tracking algorithms [17] tailored to use the pilot structure of the 802.11p standard in V2V environments. Relative to [17], we present a more extensive explanation of the previously proposed schemes as well as a detailed analysis of their limitations. Slight enhancements in the channel estimation schemes are also introduced, e.g. in Section IV-A. An analysis was also presented on why the proposed schemes outperform the previously proposed ones, as well as insight into their relative performance in different scenarios. Additional simulation results are also presented.

In the first proposed algorithm, we implement a semi-blind channel estimation algorithm based on the blind finite alphabet-based scheme of [18], but where we use knowledge of the pilots to resolve phase ambiguities and apply time-domain truncation of the channel impulse response to improve performance. In the second algorithm, the pilot information and the frequency correlation among adjacent subcarriers are exploited to track the channel variations in a simple way leading to a low-complexity algorithm. In the third algorithm, we propose decision-directed channel estimation combined with time-domain truncation to alleviate some of the effects of error propagation associated with decision feedback. Our proposed channel estimation and tracking algorithms are shown to result in better performance than previously proposed channel estimation algorithms with lower implementation complexity.

The rest of this paper is organized as follows. In Section II, we describe the V2V system model, transmitter blocks, and receiver blocks. In Section III, we present the different approaches for V2V channel estimation. In Section IV, we describe our proposed semi-blind channel estimation algorithms. In Section V, simulation results are presented for performance comparisons, and we present some discussion and our conclusions in Section VI.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>IEEE 802.11a</th>
<th>IEEE 802.11p half clock mode</th>
<th>Changes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bit rate (Mbit/s)</td>
<td>6, 9, 12, 18, 24, 36, 48, 54</td>
<td>3, 4, 5, 6, 9, 12, 18, 24, 27</td>
<td>Halved</td>
</tr>
<tr>
<td>Modulation mode</td>
<td>BPSK, QPSK, 16QAM, 64QAM</td>
<td>BPSK, QPSK, 16QAM, 64QAM</td>
<td>Unchanged</td>
</tr>
<tr>
<td>Code rate</td>
<td>1/2, 2/3, 3/4</td>
<td>1/2, 2/3, 3/4</td>
<td>Unchanged</td>
</tr>
<tr>
<td>Number of subcarriers</td>
<td>52</td>
<td>52</td>
<td>Unchanged</td>
</tr>
<tr>
<td>Symbol duration</td>
<td>4 µs</td>
<td>8 µs</td>
<td>Doubled</td>
</tr>
<tr>
<td>Guard time</td>
<td>0.8 µs</td>
<td>1.6 µs</td>
<td>Doubled</td>
</tr>
<tr>
<td>FFT period</td>
<td>3.2 µs</td>
<td>6.4 µs</td>
<td>Doubled</td>
</tr>
<tr>
<td>Preamble duration</td>
<td>16 µs</td>
<td>32 µs</td>
<td>Doubled</td>
</tr>
<tr>
<td>Subcarrier spacing</td>
<td>0.3125 MHz</td>
<td>0.15625 MHz</td>
<td>Halved</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>20 MHz</td>
<td>10 MHz</td>
<td>Halved</td>
</tr>
<tr>
<td>Pilots per OFDM symbol</td>
<td>4</td>
<td>4</td>
<td>Unchanged</td>
</tr>
</tbody>
</table>

TABLE I: Physical layer comparison between IEEE 802.11a and IEEE 802.11p.

II. SYSTEM AND CHANNEL MODEL

As mentioned earlier, because the IEEE 802.11p physical layer [19] was adapted from the IEEE 802.11a [20] standard, both have very similar packet structure. Table I presents a comparison of the physical layer parameters of the IEEE 802.11a and IEEE 802.11p standards.

A. IEEE 802.11p vs IEEE 802.11a

The IEEE 802.11p standard uses subcarriers numbered from -26 to 26, where the zero frequency subcarrier is not used; also, subcarriers -32 to -27 and 27 to 31 are used as guard bands. Only four pilots exist in each OFDM symbol and are in the subcarriers -21,-7,7 and 21. The remaining 48 subcarriers are used for data transmission.

The convolutional encoder, the interleaver and the mapper parameters are determined by the rate parameter that indicates the transmission rate. Through the use of a guard interval, OFDM systems mitigate intersymbol interference caused by multipath fading. However, IEEE 802.11a was designed for stationary indoor environments with low delay spread. Wireless Access Vehicular Environments (WAVE)
[21] involve outdoor environments, which have high delay spreads that would exceed the length of the guard time in IEEE 802.11a. For this reason, 802.11p was down-clocked to half the clock speed of 802.11a, and the guard time was consequently doubled from 0.8 to 1.6 µs, to accommodate the larger delay spreads. Because 802.11a is a packet-based transmission, channel estimation is enabled by utilizing the known training symbols transmitted at the beginning of each packet. The channel is estimated only once for each packet and is used to equalize the whole packet. Because of the highly time-varying channel in V2V environments, however, coupled with the fact that the 802.11p standard does not limit the packet length, the channel estimate performed for each packet can be quickly outdated. In addition, the 802.11p standard, similar to 11a, uses only four pilot subcarriers in each OFDM symbol. These pilot subcarriers are not spaced close enough to adequately reflect channel variation in the frequency-domain. Therefore, the main challenge is to identify an accurate method for updating the channel estimate over the entire packet length.

B. Transmitter and Receiver Blocks

To combat deep fades in a wireless environment, the encoded bits are interleaved using a block interleaver. The block interleaver corresponds to one OFDM data symbol where the size of the block depends on the modulation scheme selected. The interleaved bits are digitally modulated and divided into 48 sub-channels with four fixed pilot tones. The parallel data are then multiplexed into a 64-point inverse fast Fourier transform (IFFT). The output of the IFFT is then converted to serial data. Finally, the cyclic prefix is added.

At the receiver the cyclic prefix is removed from the received signal. The serial data is converted to parallel data for the FFT input, yielding the following output in the frequency-domain

\[ Y(t, k) = H(t, k)X(t, k) + Z(t, k) \] (1)

where \( Y(t, k) \) and \( X(t, k) \) denote the FFT of the received and transmitted OFDM data symbols, respectively, \( t \) represents the symbol index, \( k \) represents the subcarrier number, \( H(t, k) \) represents the channel frequency response and \( Z(t, k) \) represents the complex circularly symmetric additive white Gaussian noise (AWGN). At the receiver, the data is equalized, soft-demodulated, deinterleaved and finally decoded using the Viterbi decoder.

C. V2V Channel Model

In practical mobile radio channels, the received signal consists of a combination of attenuated, reflected, refracted, and diffracted replicas of the transmitted signal. Furthermore, the channel causes a spectral (Doppler) spread or broadening if either of the transmitter or receiver is moving [22].

Characterization of the V2V channel is essential for the design of channel estimation algorithms and performance modeling of the end-to-end V2V system. Since the emergence of mobile cellular networks several decades ago, most of the research efforts for vehicular communications has been directed towards characterization of the channel between a static base station and a mobile device. Indoor channels were studied more recently for WiFi and indoor cellular applications. V2V channel measurement campaigns were therefore recently conducted under various V2V scenarios. Not surprisingly, it turned out that the V2V channel is very different from the available cellular and indoor channel models in terms of both frequency and time selectivity, as well as fading statistics.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Distance between Tx &amp; Rx (m)</th>
<th>Velocity (Km/hr)</th>
<th>Doppler Shift (Hz)</th>
<th>Max. Excess Delay (µS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>V2V Expressway Oncoming</td>
<td>300-400</td>
<td>104</td>
<td>1000-1200</td>
<td>0.3</td>
</tr>
<tr>
<td>V2V Urban Canyon Oncoming</td>
<td>100</td>
<td>32-48</td>
<td>400-500</td>
<td>0.4</td>
</tr>
<tr>
<td>RTV Suburban Street</td>
<td>100</td>
<td>32-48</td>
<td>300-500</td>
<td>0.7</td>
</tr>
<tr>
<td>RTV Expressway</td>
<td>300-400</td>
<td>104</td>
<td>600-700</td>
<td>0.4</td>
</tr>
<tr>
<td>V2V Expressway same direction with wall</td>
<td>300-400</td>
<td>104</td>
<td>900-1150</td>
<td>0.7</td>
</tr>
<tr>
<td>RTV Urban Canyon</td>
<td>100</td>
<td>32-48</td>
<td>300</td>
<td>0.5</td>
</tr>
</tbody>
</table>

TABLE II: 802.11p standard channel models (RTV stands for roadside-to-vehicle)

There are several reasons for why the vehicular channel is very different from the cellular channel and the indoor channel. First, and as mentioned earlier, both the transmitter, the receiver, and the scatterers are moving, which results in a fast varying channel impulse response. Second, the transmitting and the receiving antennas are at the same height. This results in scattering at both transceivers, the angle of arrival spread being large at both transceivers due to similar clutter at both locations, and the propagation lying on the horizontal plane within a short communications range (less than 100 m). Third, the vehicular channel suffers from long delay spread compared to the indoor channel. Fourth, the spectral band of vehicular communications is 5.9 GHz, so the signal suffers from higher path loss than cellular systems operating at 700-2100 MHz or WiFi systems operating in the 2.4 GHz band. This also causes higher Doppler shift for a given speed.

Based on the relative motion of the transmitter and receiver, the existence and nature of scatterers, and overall environment, e.g. urban versus suburban, there are several V2V channel models that differ in various metrics such as fading statistics, multipath delay spread and Doppler spread. V2V channel modeling efforts are reported in [23]–[32].

In our simulations, we adopt the standard IEEE 802.11p channel models in [27], [28], where six channel models are defined for different vehicular scenarios as shown in Table II. In the tapped-delay line model, each tap process is described by a Doppler power spectral density having Rayleigh fading and the channel impulse response has 8 resolvable taps.
III. CHANNEL ESTIMATION TECHNIQUES

Channel estimation algorithms can be classified into three categories; training-based, blind, and semi-blind algorithms [33]. For time varying channels, training-based schemes require the frequent transmission of training sequences which results in increased overhead. On the other hand, blind channel estimation techniques rely on the statistical properties of the information sequences to estimate the channel coefficients, and possibly a priori knowledge of channel statistics. However, they are in general computationally expensive and suffer from slow convergence speed. Semi-blind channel estimation techniques strike a balance between computational complexity and high overhead.

In this section, we present some channel estimation and tracking techniques, including variations that were proposed for V2V channels. We also discuss the limitations of each of these schemes. In the next section, we present our proposed channel estimation techniques that overcome the limitations of the estimators presented here.

A. Block Type Training-based Channel Estimation

Under the assumption of slow channel fading, block type training-based channel estimation is possible in OFDM systems by sending known OFDM symbols within a specific period of time, e.g. at the beginning of a packet. At the receiver side, channel estimation is performed using the received signals and pilots, and may or may not need certain knowledge about the channel statistics. These channel estimates are then used for equalization of all the remaining OFDM symbols in the same packet until another pilot symbol is received.

Least squares (LS) estimation is normally used to estimate the channel using the two identical preamble symbols sent at the beginning of each packet in IEEE 802.11p. The first two received symbols $Y_{P1}$ and $Y_{P2}$ are divided by the known training sequence $X_P$ then averaged to get the channel estimate for all subcarriers given by

$$\hat{H}_{LS}(k) = \frac{Y_{P1}(k) + Y_{P2}(k)}{2X_P(k)}$$  \hspace{1cm} (2)

where $\hat{H}_{LS}(k)$ is the LS channel estimate on the $k$-th subcarrier. LS estimators are low-complexity estimators that do not need any knowledge about the channel statistics but suffer from high mean square error. For the IEEE 802.11a standard this estimate may be used to equalize the remaining data symbols in the same packet, since the channel is nearly constant throughout the packet length. In V2V channels, the LS estimate will be outdated after a few symbols and it cannot support relatively large packets or relatively high speeds. Hence, we use the LS as a reference for comparison to other schemes.

Using the channels second order statistics, namely the time and frequency auto-correlation functions, MMSE offers improved channel estimation performance. As is well-known, the MMSE estimator provides much better performance than the LS estimators, especially under low SNR conditions, at the expense of higher computational complexity due to matrix inversion during each execution. However, for fast varying channels, it is infeasible to estimate the time and frequency correlation functions.

In [34], decision-directed channel estimation was presented to track fast channel variations in the same packet. The initial channel estimate is calculated using the LS or MMSE estimators and the channel estimate is updated for subsequent OFDM symbols in the same packet by demodulating each OFDM symbol based on the channel estimate from the previous symbol; then, the demodulated symbol is used to obtain an updated channel estimate to be used for demodulating the next symbol, and so on. While offering some improvement, this scheme suffers from the well-known error propagation problem and the performance in terms of BER under fast varying environments is still unsatisfactory, as found from the BER floors that occur under many scenarios.

B. Pilot-based Channel Estimation with Spectral and Temporal Averaging

In order to track the channel variations in the time and frequency domains, the pilots must be spaced closely enough so that the Nyquist sampling criterion is satisfied. In [14], several techniques were proposed that relied on LS channel estimates for pilot subcarriers and interpolation for neighboring data subcarriers, decision feedback, as well as time averaging over multiple symbols. The best technique in [14] was Spectral Temporal Averaging (STA), which we describe briefly in the following and in which we compare our proposed estimators.

STA is based on the correlation between the channel gains on each subcarrier and its neighboring subcarriers in the frequency-domain and the channel time correlation across successive OFDM symbols. To equalize any given symbol, the previous symbols channel estimate is used, as follows

$$\hat{S}(t, k) = \frac{Y(t, k)}{\hat{H}(t - 1, k)}$$  \hspace{1cm} (3)

where $\hat{S}(t, k)$ is the equalized symbol at subcarrier $k$ and time $t$ and $\hat{H}(t - 1, k)$ is the channel estimate from the previous symbol. The first (preamble) symbols channel estimate is the LS estimate based on the known preamble. Then, the current symbols channel estimate is updated using decision feedback as follows

$$\hat{H}(t, k) = \frac{Y(t, k)}{\hat{X}(t, k)}$$  \hspace{1cm} (4)

where $\hat{X}(t, k)$ is the demodulated data symbol based on $S(t, k)$.

Frequency correlations are also exploited via windowing in the frequency domain. As we demonstrate in the simulations section, however, STA still fails to adequately track the channel for highly time-varying environments resulting in PERs higher than $10^{-3}$ at SNRs up to 30 dB in many scenarios.

C. Finite Alphabet-Based Blind Channel Estimation

Blind channel estimation techniques are considered only if the channel is static over a long enough period to obtain a reliable estimate of the statistical behavior of the received
signals. That is why totally blind estimation techniques are unusable in fast fading channels. The insufficient number of pilots in the IEEE 802.11p OFDM symbols motivates the use of “semi-blind” channel estimation techniques, which we present in the next section. The first such technique is based on the blind channel estimation scheme using the finite-alphabet property in [18], which we present here.

We follow the presentation in [18], where it was shown, using the finite alphabet property of the transmitted constellation, that \( X^J(t, k) = 1 \) deterministically with \( J = 2 \) for BPSK, and \( X^J(t, k) = -1 \) deterministically with \( J = 4 \) for QPSK. For any higher order QAM constellation, we have \( E[X^J(t, k)] = -1 \) with \( J = 4 \).

It may be readily shown based on the above and referring to (1) that

\[
E[Y^J(t, k)] = H^J(t, k) E[X^J(t, k)],
\]

where the expectation of the complex noise terms vanishes and the channel is assumed to be static. Hence,

\[
H^J(t, k) = \gamma E[Y^J(t, k)]
\]

where \( \gamma = 1 \) for BPSK and \( \gamma = -1 \) for all other constellations. In practice of course the channel can only be assumed to be quasi-static over a number of symbols, and \( E[Y^J(t, k)] \) is therefore estimated at the receiver using the sample mean taken over such a number of symbols. Starting in the frequency-domain, the estimator first obtains an estimate of \( H^J(t, k) \) by applying a moving average of the \( W \) most recently received blocks to obtain an estimate of the \( J \)-th power of the channel at time \( T \) as follows

\[
\hat{H}^J(T, k) = \frac{1}{W} \sum_{t=T-W+1}^{T} Y^J(t, k).
\]

In selecting the window size \( W \), there is clearly a trade-off between desirably reducing the estimator variance and undesirably averaging out the channel variations.

Next, an estimate of \( H(t, k) \) is obtained from

\[
\hat{H}(t, k) = \lambda_k [\hat{H}^J(t, k)]^{\frac{1}{2}}
\]

where \( \lambda_k \in \{\exp(j \frac{\pi}{2})^n\}_{n=0}^{J-1} \) is the corresponding scalar ambiguity in taking the \( J \)-th root. To resolve these ambiguities, exhaustive search is done over all \( J^M \) possible combinations of the phase ambiguities (\( J \) values for each subcarrier), where \( M \) is the number of subcarriers in the OFDM symbol, and where this search will be performed in the time-domain. The channel vector in the frequency domain may be written as

\[
\hat{H}_\lambda = [\hat{H}(t, 0)]^{\frac{1}{2}}, \ldots, [\hat{H}(t, M-1)]^{\frac{1}{2}}]^{T}.
\]

The corresponding time-domain channel vector may be written as follows

\[
\hat{h}_\lambda = \frac{1}{M} V_H^\dagger \hat{H}_\lambda
\]

where \( V_1 \) is a scaled version of the first \( L+1 \) columns of the FFT matrix \( F_M \) of size \( M \) with \((m, n)\) entry \( \exp(-j 2\pi (m-1)(n-1)/M) \), and where \( L \) is the channel order, i.e.,

\[
V_1 = \sqrt{M} F_M(:, 1 : L + 1).
\]
of the number of channel taps in the time-domain, i.e. the channel maximum delay spread, to improve the performance using the time-domain truncation (TT) technique.

A. Finite Alphabet Estimation with Time-Domain Truncation (FA-TT)

We first apply this enhancement to the finite-alphabet scheme of [18] and additionally exploit the pilots information in each OFDM symbol to resolve the single residual phase ambiguity of the entire vector of channel estimates. As explained in the previous section, the initial channel estimates are obtained based on the finite alphabet property of the transmitted data symbols using (7) and (12). From our simulations, a moving average window size of $W = 3$ consecutive OFDM symbols for time averaging was found to be the best size for estimating the sample mean while allowing for tracking fast channel variations.

After the FFT of the 8-tap channel estimates $\hat{h}$ is computed to yield the 64-subcarrier frequency response $\hat{H}$, the pilot information in each symbol is used to resolve the single residual phase ambiguity of the channel impulse response by comparing the initial channel estimates $\hat{H}$ at the 4 pilot symbols with their LS channel estimates, where LS estimation is done only on the 4 pilot subcarriers. The single residual phase for which the channel estimates on the pilots are closer, in the mean-square error sense, to their LS estimates will be selected.

Next, and in order to exploit the limited number of channel taps in the time-domain [27], time-domain truncation is used to improve the channel estimation and tracking [35]. In time-domain truncation, we zero out samples of the channel impulse response after the 8th tap, which is the last tap in the timedomain according to our V2V channel model, and go back to the frequency domain to obtain

$$\hat{H}_{freq} = V_1 \hat{h}(1:8),$$

where $V_1$ is a scaled version of the first $L + 1$ columns of the FFT matrix as in (11) with $L = 7$. We then update the channel estimates on each subcarrier based on

$$\hat{H}_{new}(t, k) = \arg \min_{\hat{H}(t,k)} ||\hat{H}_{freq}(t, k) - \hat{H}(t,k)||$$

where $\hat{H}_{new}(t, k)$ is the new estimate on the $k$-th subcarrier and $\hat{H}(t, k)$ belongs to the set of $J$-th roots of $H^J(t, k)$, which has $J$ elements. It is important to note that the minimization in (15) occurs in the frequency domain, unlike (12). Furthermore, it is carried out on each subcarrier separately. Hence, the search space size is not exponential in the number of subcarriers and we may use all $M$ subcarriers rather than $N$ as we had to do previously, which results in a performance gain. Now, we have a new frequency-domain estimate and we use IFFT to get an updated time-domain estimate. Then, time-domain truncation is repeated and we go back and forth between the frequency and time domains until convergence.

To understand the gains achieved by time-domain truncation, note that the effect of channel estimation errors in the frequency-domain is reflected as a higher number of taps in the time-domain channel impulse response. For example, consider the extreme case of having only one erroneous channel gain in the frequency-domain; this is equivalent to a Kronecker delta error signal added to the true channel in the frequency-domain. In the time-domain, this frequency-domain Kronecker delta error signal will spread over the entire symbol duration and will not be limited to the CP duration (where the CP includes the entire time-domain error-free channel impulse response). Truncating the channel in the time-domain will remove most of the Kronecker delta error signal in the impulse response while not causing any loss in the true time-domain channel taps. More generally, frequency-domain channel estimation errors cause lengthening of the channel impulse response and that is why truncation enhances the channel estimation performance.

It was found by simulation that this loop converges within only two iterations. This technique enhances the channel tracking even with a coarse initial channel estimate in a highly dynamic environment, as we shall see in the simulation section. Furthermore, each iteration entails one $M$-point IFFT and one $M$-point FFT. For the IEEE 802.11p standard $M = 64$, so time-domain truncation requires relatively low computational complexity as we go from the time-domain to the frequency-domain and vice versa.

The problem with this algorithm is that the computational complexity greatly depends on the value of $J$. As mentioned before, $J = 2$ for BPSK and $J = 4$ for higher order constellations. The number of possible channel vectors is, in general, $J^N$, where $N$ is at least 8 in our case. This renders this estimator impractical for QPSK or higher order constellations. This is why in the simulations section we only show the results for the FA-TT estimator for the case of BPSK ($J = 2$). Furthermore, for constellations higher than QPSK, we need to average over multiple OFDM symbols to obtain a reliable sample mean approximation to $E[X^J(t, k)]$ in (5). However, this is impractical in our V2V channel model due to fast channel variations.

To address the above two problems, we propose two novel low-complexity channel estimators that work on a symbol-per-symbol basis. The first estimator makes use of the finite alphabet property of the transmitted signals, albeit in a different way, and applies time-domain truncation to enhance the channel estimation performance. The second estimator combines decision-directed channel estimation with time-domain truncation. Although, the two proposed schemes have low-complexity, they result in superior performance compared to the FA-TT and other previously proposed channel estimators.

B. Alphabet Search Estimation with Time-Domain Truncation (AS-TT)

Here, we propose a computationally efficient channel estimation algorithm based on the finite alphabet property of the transmitted signal that also utilizes the correlation between the channel gains of adjacent subcarriers in the frequency domain. The finite alphabet property provides a list of candidate LS channel estimates on each subcarrier (one for each possible constellation point). We then exploit the frequency domain channel correlation to select one element from each subcarrier
list to be the channel estimate based on the method explained below.

First, the 48 data subcarriers are divided into four groups with the pilot subcarrier in the middle. Starting from the pilot position, the channel estimates of the neighboring subcarriers are determined based on the minimum Euclidean distance between the pilot channel estimate and the possible channel estimates of its neighboring subcarriers according to the following equation

$$\hat{H}(t, k \pm 1) = \arg \min_{\hat{H}(t,k \pm 1)} \left\| \hat{H}_{LS}(t,k) - \hat{H}(t,k \pm 1) \right\|$$  \hspace{1cm} (16)

where \(\hat{H}(t,k \pm 1)\) belongs to the set of possible LS channel estimates at the \(k \pm 1\)-th subcarrier. This set of channel estimates is formed based on the finite alphabet property of the transmitted symbols as \(\{Y(t,k \pm 1)/X_c(t,k \pm 1)\}\), where \(X_c(t,k \pm 1)\) is the candidate data that runs over all the possible constellation points, i.e., \(X_c(t,k \pm 1) \in \{\pm 1\}\) for BPSK and \(X_c(t,k \pm 1) \in \{\pm 1/\sqrt{2}, \pm 1/\sqrt{2}\}\) for QPSK, etc. For example, for BPSK, we have two possible LS channel estimates for each received \(Y(t,m)\) given by \(Y(t,m)\) and \(-Y(t,m)\), depending on whether +1 or -1 was transmitted. If subcarrier \(m\) is adjacent to a pilot subcarrier, we select the channel estimate, from the set \(\{Y(t,m), -Y(t,m)\}\), based on which is closer to the LS pilot channel estimate. Then we use the estimated channel response of the neighboring subcarrier to estimate the subcarrier next to it and so on until all the neighboring subcarriers in a pilot group are estimated. The same is applied to each group.

To enhance the tracking capability of the proposed alphabet search estimator, time-domain truncation is performed as described in (14). The alphabet search estimator provides an initial channel estimate for the time-domain truncation loop. Time-domain truncation iterations will enable the estimator to track fast channel variations more closely. The time-domain truncated channel provides a new frequency-domain channel estimate. An updated estimate on each subcarrier is then obtained by selecting the channel estimate that is closest to the new estimate, again from the set of candidates LS channel estimates based on the finite alphabet property. This is applied to all the channel estimates on all the subcarriers, pilot and data alike. Then, we can go again to the time-domain to truncate the channel impulse response as in (14). These same steps of moving back and forth between time-domain truncation and frequency-domain alphabet search may be repeated till there is no appreciable change in the channel estimates. As before, it was found by simulations that two iterations are sufficient for convergence in almost all cases.

It should be noted that the complexity of the alphabet search estimator is low compared to the previously proposed estimator as we avoid the exhaustive search over \(N^N\) different channel vectors. Alphabet search with time-domain truncation algorithm achieves very good performance in stationary environments and is also able to track fast channel variations in vehicular environments; this is valid also for very large packet sizes, as we shall see in the simulations section.

C. Decision Directed Estimation with Time-Domain Truncation (DD-TT)

Decision-directed channel estimation was extensively studied in literature, e.g. [36]–[39], and has been demonstrated to have an advantage over pilot aided schemes in terms of performance and bandwidth efficiency. However, error propagation is a well-known problem that affects decision-directed channel estimation, specially at low SNR, and that might result in the loss of the entire packet.

In the proposed scheme, we use decision directed channel estimation to obtain an initial estimate, then a simple time-domain truncation loop is applied to enhance the estimate and reduce the effect of error propagation.

We start with the LS estimates \(\hat{H}_{LS}\), which are obtained from channel estimation on the preamble symbols, as an initial estimate; then channel equalization of the first data symbol is done using (3). The channel gain \(\hat{H}(t,k)\) is then estimated using \(\bar{X}(t,k)\), which is the demodulated symbol as in (4). We use the hard demodulator decision without error correction to avoid increased complexity and/or latency.

Time-domain truncation as in (14) is then applied to the channel estimates in the time domain to reduce the effect of error propagation. Any demodulation error will be equivalent to adding high noise to the true subcarrier channel estimate. Going from frequency domain to time domain will uniformly distribute the effect of this “noise” across the different taps in the time domain. Time-domain truncation will remove most of this noise as most of the time domain taps are removed.

Going back to the frequency domain, the updated channel coefficient on each subcarrier is then used in (3) to obtain an updated channel estimate. We may once again go to the time-domain and truncate the impulse response. These iterations are applied until convergence, where there is no appreciable change in the channel estimates. Once again, since the channel estimates converge most of the time after only 2 iterations, based on our simulations, this algorithm has low complexity.

V. SIMULATION RESULTS

In this section, the 802.11p end-to-end physical layer was simulated and the Packet Error Rate (PER) taken as the performance measure of the system. The system uses the 802.11p rate 1/2 convolutional encoder and interleaver. The receiver uses the soft-decision Viterbi algorithm to decode the data packets. The system was simulated with varying SNRs, vehicle velocities, packet lengths and modulation sizes (i.e., varying data rates). The simulation range of SNRs was drawn from 0 to 30 dB. The maximum simulated velocity was 104 km/h. The packet lengths ranged from 10 to 200 OFDM data symbols. The focus, however, was to test the performance under worst-case V2V scenarios, which involved a fading channel with no LOS (i.e. Rayleigh fading channel), high Doppler frequency, and a large packet size.

Performance comparisons between our proposed channel estimators and the previously proposed schemes presented in Section III are presented. It is worth mentioning that LS and
MMSE channel estimation based on the preamble alone result in unacceptably high error floors for all but impractically small packets and Doppler frequencies. Due to space limitations we do not present those results separately; rather in the following figures the LS channel estimate performance is shown for perspective, but it is unusable in all scenarios.

Fig. 1 shows performance comparisons for a medium mobility BPSK scenario with large packet sizes. The FA-TT scheme has a performance advantage of about 1 dB over the STA scheme at a PER of $3 \times 10^{-2}$. The performance gain of the FA-TT is not very large due to the need for averaging over a large number of symbols to approximate the vanishing of the noise terms in (5). However, a window size $W > 3$ in (7) degrades performance due to failing to track fast channel variations as mentioned in Section IV-A. The AS-TT on the other hand achieves a gain of about 7.5 dB compared to the STA algorithm at a PER of $3 \times 10^{-2}$. This is due to noise suppression achieved by utilizing the demodulated data for calculating the channel estimate. Moreover, limiting error propagation is achieved by exploiting knowledge of the small number of taps of the V2V channel model using time-domain truncation. The DD-TT scheme offers an additional 5 dB gain over the AS-TT scheme.

The performance gains increase further for higher mobility scenarios. For example, Fig. 2 and Fig. 3 show that the DD-TT scheme achieves gains in excess of 15 dB at PERs around $2 \times 10^{-1}$ compared to the STA algorithm for BPSK with large packet sizes. This is due to exploiting the channel estimates at the four pilots in every OFDM symbol along with the frequency correlation between adjacent subcarriers in the channel response. From Fig. 3, it can be clearly seen that the STA algorithm performance is inadequate and cannot be used for such packet sizes.

Fig. 4 compares the performance of DD-TT and AS-TT for a high mobility scenario with QPSK data and large packet sizes. Both schemes outperform the STA by about 13-15 dB in the $2 \times 10^{-1}$ PER vicinity. This performance advantage is achieved despite their low computational complexity as explained earlier. Note that the FA-TT is absent in this comparison since this scheme complexity increases with the constellation size and is practically unusable with higher order modulation schemes.

Fig. 5 compares the performance of DD-TT and AS-TT once again for a high mobility scenario but with the 16-QAM modulation with large packet sizes. Again, both schemes outperform the STA scheme with a large margin. Similar to previous simulations results, DD-TT shows to consistently outperform all the other schemes.

VI. DISCUSSIONS AND CONCLUSIONS

In this paper, we have presented several channel estimation and tracking algorithms for V2V channels. Finite alphabet with time-domain truncation (FA-TT), decision-directed with time-domain truncation (DD-TT), and alphabet search with time-domain truncation (AS-TT) channel estimators were proposed for the 5.9 GHz 802.11p receiver. The proposed channel estimators were compared to channel estimators previously presented in Section IV-A. The performance gains of these schemes are due to the exploitation of the channel correlations and the use of time-domain truncation to limit the error propagation. The DD-TT scheme offers the highest performance gains, while the AS-TT scheme provides limited error propagation. The FA-TT scheme provides a good compromise between performance and computational complexity.

In summary, the proposed channel estimation and tracking algorithms offer significant performance improvements over existing methods, particularly in high mobility scenarios. Future work will focus on further optimizing these algorithms and evaluating their performance in real-world V2V environments.
proposed for V2V channels using simulations. Simulation results show that the proposed estimators improve the PER performance for all modulation orders across all channel models and for all packet sizes. In fact, it was shown that previously proposed channel estimators were unusable in most V2V environments with the pilot structure of the 802.11p standard. Reasonable performance gains are achieved for the FA-TT scheme over the STA scheme for BPSK and QPSK. However, the FA-TT scheme is too complex for higher modulation orders. Significant performance gains are demonstrated for the proposed DD-TT and AS-TT estimators when compared to the STA algorithm of [14]. For BPSK and QPSK, the AS-TT scheme outperforms the DD-TT scheme at high SNR whereas the DD-TT has a slight advantage at lower SNR. For shorter packet sizes the DD-TT scheme is superior to the AS-TT. Both schemes have relatively low complexity and are based on the IEEE 802.11p standard, and are therefore good candidates for WAVE communication systems.

Note that in keeping with the low-complexity theme in our paper, our decision-directed channel estimation is based on hard decisions applied before the Viterbi decoder, i.e. without error correction. Otherwise, there would have to be two passes on the Viterbi decoder instead of one for each bit. This could be a huge increase in complexity as the Viterbi decoder is one of the bigger blocks in the receiver. Alternatively, if truncated depth decoding is applied, typically for very large packets, the latency would also be increased. Otherwise, using channel estimates based on error-corrected decisions would bring the performance of the DD-TT scheme much closer to that of the perfect channel estimator.

**References**

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