Doppler Shift Compensation in Vehicular Communication Systems

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***Abstract*—Vehicular Communication Systems also known as *Vehicle-to-Vehicle communication systems (V2V)* are standardized by the IEEE 802.11p standard which specifies the use of *Orthogonal Frequency-Division Multiplexing (OFDM)* in the physical layer. Doppler shift due to high mobility along with multipath propagation in vehicular environments result in a time-varying multipath or a doubly selective channel. The estimation of such a channel and its subsequent equalization is a non-trivial task [1]. Several techniques for the estimation and equalization of a doubly selective channel have been proposed in literature. However, these techniques either perform poorly or work with a complexity that is prohibitive for consumer hardware [2]. We propose the Matching Pursuit (MP) algorithm, a Compressed Sensing (CS) scheme to perform the task of channel estimation. We also propose modifications to this algorithm that are focused to reduce the computational complexity. We further show that the channel estimate from the MP algorithm can be used by both conventional and state-of-art equalizers. The proposed algorithms are implemented as a Software-Defined Radio (SDR), that provides an excellent platform for design, development and the ability to perform simulation as well as real-world experiments. Simulation results assess the performance gains of the proposed channel estimation and equalization schemes.**

***Index Terms*—V2V Communication, OFDM, Doppler Shift, ICI, SDR, Channel Estimation and Equalization**

I. INTRODUCTION AND RELATED WORK

Vehicular communication systems have recently attracted a great deal of research attention by government agencies, policy makers and automobile manufacturers. There is a growing demand for solutions that are aimed to provide safety and non-safety applications for vehicles [3]. The IEEE802.11p standard specifies Wireless Access in Vehicular Environments (WAVE) and defines the use of OFDM in the physical layer.

OFDM is a form of non-trivial frequency-division multiplexing. While classical telecommunication systems always divide the allocated bandwidth between different applications/channels, OFDM offers a way to split up the bandwidth of a single application. Thus in an OFDM system, the allocated bandwidth is divided into a number of narrowband sub-carriers with harmonic frequencies that provide a mathematical orthogonality, preventing them from interfering with each other. The use of OFDM comes with several advantages in terms of coping with narrowband interference, efficient spectral shaping and low-complexity implementation. However, the relative mobility between the vehicles that are communicating with each other, results in Doppler shift that affects the performance of the OFDM system by destroying the orthogonality between the narrowband sub-carriers and ultimately resulting in Inter-Carrier Interference (ICI). Moreover, V2V systems are designated to work in the 5.8 GHz domain with a relative velocity up to a few 100 km/h, which proportionally increases the Doppler shift. Thus, techniques to combat the effects of high mobility namely channel estimation and equalization are relevant for vehicular communication systems. In China, vehicular communication is specified by the Dedicated Short Range Communication (DSRC) standard that is governed by the Standardization Administration of the People's Republic of China [4]. This standard also specifies the use of OFDM in the physical layer and thus all the algorithms proposed in this paper are suitable for this standard.

Channel estimation is a fundamental step towards overcoming the effects of high mobility at the receiver. A detailed overview of the most common channel estimation schemes is presented in [2]. Conventional methods like the Least Squares (LS) estimator work well with Additive White Gaussian Noise (AWGN) channels but perform poorly in rapidly time-varying multipath channels [5]. The Basis Expansion Model (BEM) is also widely proposed as a channel estimation technique [6], [7]. It approximates the channel taps by a linear combination of appropriate basis functions. However, these methods are shown to be inaccurate for doubly selective channels and the proposed improvements make these methods computationally expensive [1], [8]. Moreover, the BEM techniques for channel estimation do not utilize the inherent sparsity of the time-varying multipath channel [9]. In this paper, we propose the Matching Pursuit (MP) algorithm, a Compressed Sensing (CS) scheme to perform the task of estimating the channel. Compressed sensing techniques for channel estimation build on the philosophy that sparse signals can be efficiently reconstructed using a handful of precise measurements. It exploits the fact that time-varying multipath channels are mostly dominated by a few significant paths as shown in [10], [11]. The MP algorithm was first proposed by W. Li.et.al [12] to estimate the delays in a sparse shallow water acoustic channel. The use of matching pursuit algorithms for the estimation of wireless communication channels can also be seen in [13], [14], [15].

Channel equalization leverages the channel state information to perform equalization. Simple equalizers like the one-tap equalizer are only suitable for AWGN channels. Conventional equalizers like the Linear Minimum Mean Square

Error (LMMSE) equalizer involve a matrix inversion making it computationally expensive. The Successive Interference Cancellation Interference Reduction (SICIR) [16] is the state-of-art equalizer proposed in 2014. This equalizer is shown to offer good performance with a complexity that is linear in the best case. In this paper, the channel matrix computed by the MP algorithm is validated by both the LMMSE and the SICIR equalizer.

This paper is organized as follows. In Section II, a typical channel model seen in environments of high mobility is intuitively derived and the problem statement is formulated. Section III describes the techniques for channel estimation and equalization. Section IV describes the implementation details and presents the results. Finally, a few remarks and the scope for future research is summarized in Section V.

II. Problem Formulation

The next generation wireless communication for Intelligent Transport Systems (ITS) envisions a vast network of vehicles that can communicate with each other and roadside access points by providing a Wireless Local Area Network (WLAN) like environment. WLAN networks use OFDM as the transmission technology in the physical layer due to the various inherent advantages as pointed out in Section I. However, OFDM is predominantly used in an indoor environment that is characterized by little to no mobility.

A. The IEEE 802.11p standard

IEEE 802.11p specifies wireless access in vehicular environments, paving the way for intelligent transport systems. The physical layer of the IEEE 802.11p standard is a close adaptation of the well known IEEE 802.11a standard for indoor WLAN's. However, the IEEE 802.11p standard should work in highly mobile vehicular environments. Some of the most prominent changes and their consequences are listed below.

- **Symbol Duration** is doubled when compared to the IEEE 802.11a standard. This implies that the guard interval is doubled as well, allowing for longer echoes to be gathered at the receiver. Thus the IEEE 802.11p standard is more resilient to multipath echoes.
- **Bandwidth** is halved when compared to the IEEE 802.11a standard. Thus the IEEE 802.11p standard is more sensitive to Doppler shift since the narrowband sub-carriers are now closer to each other.

Thus, we can conclude that the enhancements made to the IEEE 802.11p standard make it more robust to multipath propagation, but at the same time it is more sensitive to Doppler shift.

B. Channel Model

A communication channel is a natural phenomenon. The typical channel characteristics seen in highly mobile environments can be intuitively derived by considering the following physical properties of electromagnetic waves:

- **Multipath Propagation** is caused due to the property of electromagnetic waves to reflect, diffract and scatter around obstacles. In a transmission scenario, this results in differently delayed and differently weighted copies of the same signal being superimposed at the receiver. From the theory of Fourier transform, a delay due to multipath propagation will result in frequency selectivity as shown in Eq. 1.

$$x(t \pm \tau_k) \circ - \bullet X(f) e^{\pm j 2\pi f \tau_k} \tag{1}$$

Here, τ_k is the delay in the k^{th} multipath.

- **Doppler Shift** is a shift in the frequency caused by the relative motion between the transmitter and the receiver. A Doppler shift causes the time selective nature of the channel as shown by the Fourier correspondence in Eq. 2.

$$X(f \pm \nu_l) \bullet - \circ x(t) e^{\mp j 2\pi \nu_l t} \tag{2}$$

Here, ν_l is the l^{th} Doppler shift. It is evident that a shift in frequency results in a time-dependent phase shift.

Thus, high mobility results in a channel that is selective both in the time as well as in the frequency domain. Such channels are called time-varying multipath channels or doubly selective channels. The channel response of such a channel for the m^{th} path and the i^{th} sample is given by Eq. 3.

$$h[i,m] = \sum_{k=0}^{K-1} \sum_{l=0}^{L-1} (U)_{k,l} e^{(j 2\pi \nu_l i)} sinc\left(m - \frac{\tau_k}{T_s}\right) \tag{3}$$

Here, K and L are the maximum number of delay and Doppler bins to be searched. T_s is the sampling interval and $(U)_{k,l}$ represents the delay-Doppler spreading function for the k^{th} delay and the l^{th} Doppler shift.

C. System Model

In an OFDM system, the data symbols are transformed from the frequency to the time domain using an N-point Inverse Fast Fourier Transform (IFFT). The transmitted signal is corrupted by a time-varying multipath channel which is modeled in Eq. 3. Given that x and y are the transmitted and the received signals, w is the white Gaussian noise, M is the maximum number of propagation paths and $h[i,m]$ is the channel response, the signal at the OFDM receiver is given by Eq. 4.

$$y[i] = \sum_{m=0}^{M-1} h[i,m] x[(i-m) modN] + w[i] \tag{4}$$

It is proven in [15] that the delays and the Doppler shifts in a doubly selective channel are independent of each other. This implies that the channel characteristics can be estimated separately. Accordingly, if only the delays are considered, the delay component of the channel is a circular matrix in the time domain. This is due to the superposition of the different echoes and the cyclic nature of an OFDM symbol. In a similar manner, if only the Doppler shifts are considered, the Doppler component of the channel is a diagonal matrix in the time domain due to shifting property of the Fourier transform. Thus the channel response in Eq. 3 can be rewritten as,

$$H_T = \sum_{k=0}^{K-1} \sum_{l=0}^{L-1} (U)_{k,l} \Lambda_l C_k \tag{5}$$

The Doppler shift matrix Λ_l is diagonal in structure and it can be constructed as,

$$\Lambda_l = diag(e^{j2\pi\nu_l t0}, e^{j2\pi\nu_l t1}, \cdots, e^{j2\pi\nu_l t(N-1)}) \quad (6)$$

The circular delay matrix $C_k \in \mathbf{C}^{N\times N}$ has the structure given in Eq. 7. Each element $c_{k,m}$ denotes the k^{th} delay for the m^{th} propagation path and is given by

$$C_k = \begin{bmatrix} c_{k,0} & 0 & \cdots & c_{k,M-1} & \cdots \\ c_{k,1} & c_{k,0} & \cdots & 0 & c_{k,M-1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & c_{k,M-1} & \cdots & c_{k,0} \end{bmatrix} \quad (7)$$

From Eq. 3 and Eq. 4, it is seen that for every propagation path m, (KL) combinations of delays and Doppler shift have to be searched at the receiver which would not scale for large K and L. However, since the channel characteristics can be estimated separately, we first search through the K delays and once the delay is found, we can search through the L Doppler shifts. This reduces the search space and consequently the computational complexity from $\mathcal{O}(KL)$ to $\mathcal{O}(K+L)$.

Moreover, since multipath delays correspond to a frequency-dependent phase shift, the delays are searched in the frequency domain. Similarly, since a Doppler shift corresponds to time-dependent phase shift, the Doppler shifts are searched in the time domain. Thus, by utilizing the tools of signal theory, the complexity associated with channel estimation is considerably reduced.

D. Problem Statement

The focus of this paper is to overcome the effects of a time-varying multipath channel caused by high mobility in vehicular environments. Towards this goal, algorithms for the estimation and equalization of such a channel are proposed that should provide a robust estimate of the channel, ensure reliable equalization and work with a complexity that is sensible for practical implementation. Ultimately, these algorithms will bring about high mobility in vehicular communication systems.

III. Methodology

A. Channel Estimation

Channel estimation is the process of learning the characteristics of the wireless channel by using the preambles and pilots that are defined in the standard. In this paper, we propose the matching pursuit algorithm [12] which is a compressed sensing scheme for channel estimation.

A prerequisite for the MP algorithm is the dictionary that serves as a reference database for all the possible combinations of channel degradations namely the delays and Doppler shift. However, details about the dictionary have not been explained by W. Li.et.al. [12] and it is simply assumed that a suitable dictionary is already present. In this paper, we propose an intuitive method to generate the dictionary. The channel model derived in Section II-B considers the physical effects seen in environments of high mobility. It is appropriate to use the same model to generate the dictionary. If a maximum of K delay and L Doppler bins have to be searched, the dictionary is denoted by $\mathfrak{D} \in \mathbb{C}^{K\times L}$, where each element of this dictionary $(\mathfrak{D})_{k,l} \in \mathbb{C}^N$ is a corrupted version of the preamble X that is defined in the IEEE 802.11p standard. The dictionary is generated as given by Eq. 8.

$$\begin{aligned} (\mathfrak{D})_{k,l} &= H_F X \\ &= \Bigg(\sum_{k=0}^{K-1}\sum_{l=0}^{L-1}(U)_{k,l} C_l \Lambda_k\Bigg) X \end{aligned} \quad (8)$$

Once the dictionary is generated, the MP algorithm is given in Table I.

Table I
The MP Algorithm

$$r_0 = y \quad (9)$$

$$b_{0,j} = \mathfrak{D}_j^H r_0 \text{ for } j = 1\ldots(K+L) \text{ and } \mathfrak{D}_j, r_0 \in \mathbb{C}^N \quad (10)$$

$$s_1 = \underset{j=1\ldots(K+L)}{\arg\max} \frac{|b_{0,j}|^2}{||\mathfrak{D}_j||^2} \quad (11)$$

$$I_1 = \{s_1\} \quad (12)$$

$$\hat{X}_1 = \frac{b_{0,s_1}}{||\mathfrak{D}_{s_1}||^2} \quad (13)$$

$$b_{1,j} = b_{0,j} - \hat{X}_1 \mathfrak{D}_j^H \mathfrak{D}_{s_1} \text{for } j = 1\ldots(K+L), j \notin I_1 \quad (14)$$

The p^{th} iteration, $p > 1$

$$s_p = \underset{j\notin I_{p-1}}{\arg\max} \frac{|b_{p-1,j}|^2}{||\mathfrak{D}_{s_p}||^2} \quad (15)$$

$$I_p = \{s_p\} \quad (16)$$

$$\hat{X}_p = \frac{b_{p-1,s_p}}{||\mathfrak{D}_{s_p}||^2} \quad (17)$$

$$b_{p,j} = b_{p-1,j} - \hat{X}_p \mathfrak{D}_j^H \mathfrak{D}_{s_p} \text{for} j = 1\ldots(K+L), j \notin I_p \quad (18)$$

The algorithm begins by initializing the residual error r_0 to the received signal y. The rank-1 projection is computed in Eq. 10, where every element of the dictionary is projected onto the received signal. In Eq. 11, the projections are maximized. The coefficient of the delay-Doppler spreading function corresponding to the element of the dictionary that maximized the rank-1 projection is computed in Eq. 13 where, $||\mathfrak{D}_{s_1}||$ is the Euclidean norm of $\mathfrak{D}_{s_1}$. The projections are updated in Eq. 14 by subtracting the contributions of the previous element s_p that maximized the projection and given that $\mathfrak{D}_j^H$ is the conjugate transpose of $\mathfrak{D}_j$. The algorithm iterates until a stopping criteria is reached or the maximum number of iterations are completed. The outcome is an estimate of the channel matrix that can be used for equalization.

B. Coherent Equalization

A coherent equalizer utilizes the channel state information to correct the received signal. Conventional equalizers like the one-tap equalizer and the LMMSE equalizer are inadequate in the context of equalizing a doubly selective channel. While the former performs poorly, the latter involves a matrix inversion which makes it computationally expensive. The Successive Interference Cancellation-Interference Reduction (SICIR) [16] is currently the state-of-art equalizer proposed in 2014 that targets a linear complexity. The basic idea of this approach is to update the received symbols by subtracting the interference components (given by the channel matrix) from the detected symbols. If the channel matrix in the frequency domain is H_F and Q is the maximum number of interference components that are considered, the equalized symbol $\hat{y}_i$ is given by Eq. 19

$$\hat{y}_i = y_i - \sum_{q=1}^{Q} (H_F)_{i,i-q} \hat{x}_{i-q} \tag{19}$$

where, $\hat{x}_{i-q}$is a previously detected symbol. The complexity of the SICIR equalizer depends on the number of interference terms considered and is $\mathcal{O}(QN)$. If the channel matrix is narrow banded, the computational complexity is nearly linear.

IV. Results

The proposed algorithms for channel estimation and equalization are implemented as an extension to the IEEE 802.11p transceiver for GNURadio [17], [18]. The dynamic channel model, that is available as a native block in GNURadio and widely accepted in the research community, is used to simulate a doubly selective channel model. The channel estimation algorithm at the receiver computes an estimate of the dynamic channel. This channel estimate is then used by different equalizers namely the LMMSE, SIC and the SICIR to perform equalization. The performance of the estimation and equalization schemes are evaluated by computing the BER at the receiver. The Perfect Channel State Information (PCSI) is chosen as the baseline to evaluate the performance of the proposed channel estimation and equalization schemes.

In Fig .1, a low Doppler shift of 20 Hz is simulated by the dynamic channel. Even in cases of low Doppler shift, it is seen that the LS estimator along with the one-tap equalizer performs poorly compared to the baseline. On the other hand, the MP estimator along with the other equalizers performs very close to the perfect channel state information. In Fig .2 and Fig .3, a Doppler shift of 200 Hz and 2000 Hz are respectively simulated and the same trend can be seen with the LS estimator performing the worst while, the MP estimator along with the LMMSE or the SICIR equalizer exhibit improved performance. Thus, we can conclude that the channel estimation and equalization schemes proposed in this paper play an important role in compensating the effects of a doubly selective channel seen in highly mobile vehicular environments.

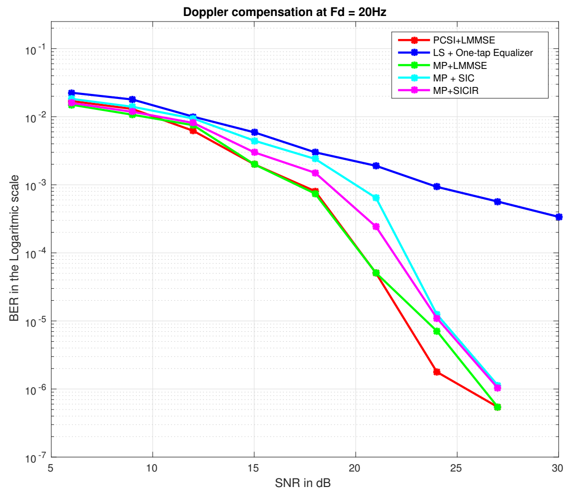

Figure 1. Performance at 20 Hz

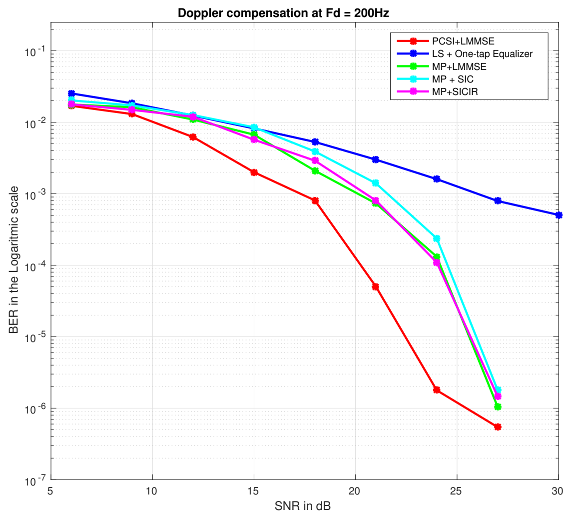

Figure 2. Performance at 200 Hz

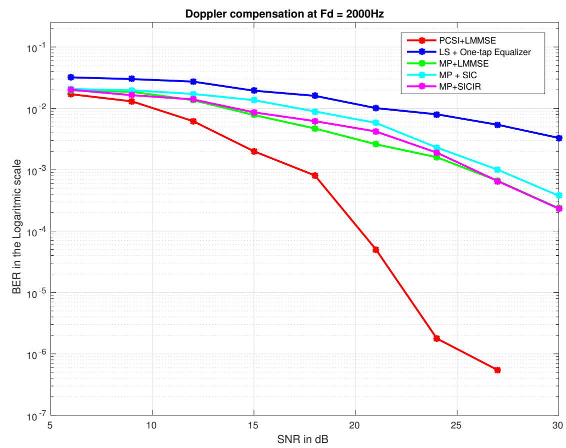

Figure 3. Performance at 2000 Hz

V. Conclusion

We propose the matching pursuit algorithm to provide a reliable estimate of the doubly selective channel with a complexity that is suitable for practical implementation. We also show that this channel estimate can be used with any suitable coherent equalizer. The results confirm that this approach is clearly feasible in terms of performance and computational complexity for different channel scenarios. An SDR implementation of the proposed algorithms provides an excellent platform for design and development of channel estimation and equalization schemes as well as the possibility for real world experimentation.

Future Work

In order to further improve the performance, a channel tracking scheme can be implemented for rapidly varying channels. The metric for the search in the MP algorithm can be further investigated to provide a more robust candidate for every iteration. The complexity can be further reduced by investigating a multi-scale search for the delays and Doppler shift. An adaptive framework for channel estimation and equalization that provides reliable equalization at optimum complexity is envisioned.

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