Channel Estimation in C-V2X using Deep Learning

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Abstract—Channel estimation forms one of the central component in current Orthogonal Frequency Division Multiplexing (OFDM) systems that aims to eliminate the inter-symbol interference by calculating the Channel State Information (CSI) using the pilot symbols and interpolating them across the entire time-frequency grid. It is also one of the most researched field in the Physical Layer (PHY) with Least-Squares (LS) and Minimum Mean Squared Error (MMSE) being the two most used methods. In this work, we investigate the performance of deep neural network architecture based on Convolutional Neural Networks (CNNs) for channel estimation in vehicular environments used in 3GPP Rel.14 Cellular-Vehicle-to-Everything (C-V2X) technology. To this end, we compare the performance of the proposed Deep Learning (DL) architectures to the legacy LS channel estimation currently employed in C-V2X. Initial investigations prove that the proposed DL architecture outperform the legacy C-V2X channel estimation methods especially at high mobile speeds.

I. INTRODUCTION

Starting with 3G, OFDM has been the choice of PHY technology due to its resilience to inter-symbol interference and multipath fading, higher data rates and better spectrum efficiency. At the heart of any OFDM receiver is the channel estimation function which estimates the CSI and uses this information to equalize the received waveform in order to mitigate the channel effects. Channel estimation can be performed in either time domain or frequency domain with the latter being used extensively in current OFDM systems due to its simplicity and ease of implementation.

In frequency domain channel estimation, known symbols called pilots are transmitted at known positions in the OFDM resource grid. These pilots can be arranged in a few frequency sub-carriers in all OFDM symbols (comb configuration), or across all subcarriers in few OFDM symbols (block configuration) or across few subcarriers on few OFDM symbols (2D grid configuration). At the receiver side, the channel is estimated by means of comparing the received pilot symbols with the transmitted pilot symbols thereby yielding the impulse response of the channel at these locations. By means of averaging and interpolation, these impulse responses are fine tuned to get the channel impulse response matrix $H$ of the whole transmitted OFDM resource grid.

There are primarily two methods for channel estimation $[1], [2]$. The first one is based on the computationally simple LS algorithm which directly divides the received pilot symbols with the transmitted pilots symbols in the frequency domain. However, this method ignores the effect of Additive White Gaussian Noise (AWGN) to which the OFDM systems are very sensitive to. In order to reduce the effect of noise, the channel impulse responses after LS estimation are averaged across time and frequency with a given 2D window size. Hence the noise is also averaged reducing its overall effect. The second method is the MMSE method that uses the statistical characteristics of the noise and the channel matrix; therefore, its computational complexity is high. Other methods such as Linear MMSE (LMMSE), Inverse MMSE (IMMSE), Chi-square distribution-based method, Haar Wavelet based method were also proposed and basically depend on LS and MMSE based methods albeit with higher complexity.

Recently, Machine Learning (ML), which has shown substantial promises during recent years $[3]$ is extensively studied by researchers in order to assess its applicability to wireless technologies. DL architectures such as CNNs, Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), Deep Belief Networks (DBNs) have been applied to various domains such as computer vision, natural language processing, social network filtering, drug design etc. where they have produced results comparable to and in some cases superior to human experts.

In this work, we investigate DL architectures to design and analyse an Artificial Neural Network (ANN) for channel estimation in high mobility vehicular scenarios. Specifically, we use C-V2X as underlying technology that specifies the use of LS based channel estimation. To this end, we frame the channel estimation as a supervised learning problem and use DL architectures based on CNN to output the channel estimation matrix $H$ which in turn is used for equalization.

A. Related State of the Art

Initially applied to upper layers $[4]$, ML has recently found applications also at the PHY Layer $[5]$–$[7]$ such as channel coding $[8]$–$[10]$, modulation recognition $[11]$, obstacle detection $[12]$ and physical layer security $[13]$ etc. The use of ML for channel estimation was initially investigated in works such as $[14]$. Subsequently, with the advent of programmable Graphical Processing Units (GPUs) and availability of open source DL libraries such as Tensorflow and caffe, many other works started applying various DL architectures for channel estimation and equalization. In $[15]$, the authors proposed an architecture by stacking two independent ANNs on top of each other for estimating the amplitude and phase values directly. The use of CNNs for channel estimation was investigated in $[16], [17]$. In $[18]$, the authors combined a ANN architecture with a genetic algorithm for channel estimation. In $[19]$, the authors used a combination of Super-resolution CNN and a
feed-forward de-noising CNN to achieve performances close to MMSE methods. The use of multi-layer perceptron for channel equalization is investigated in [13].

Our work differs from the previous work with respect to two major points. We use DL architecture based on CNN to directly output the channel matrix $H$ over different Signal to Noise Ratio (SNR) points (as opposed to single SNR value used in other works) that can be readily used for equalization. Furthermore, we use the C-V2X sidelink as underlying technology in contrast to Uu based LTE where the pilot arrangements differ and the use of MMSE is not encouraged due to high mobility scenarios.

The rest of the paper is organized as follows. Section II gives a broad overview about the C-V2X technology and the channel estimation method used. Section III outlines the simulation method using the proposed DL architecture. It also outlines the training operation and the results. Section IV concludes the paper with some future directions.

II. CHANNEL ESTIMATION IN C-V2X

C-V2X has been proposed in order to enable direct communications in 3GPP Rel.14. It introduces a new interface called PC5 in addition to the legacy Uu interface in LTE to support direct communication between devices with or without the presence of an eNodeB (eNB). In Rel.15, it was further enhanced to support V2X applications by increasing the Demodulation Reference Symbols (DMRS) symbols fro 3 to 4 to better tackle the fast channel variations in vehicular scenarios. V2X communications happen in periodic intervals (called the sidelink period) that ranges between 40 ms to 320 ms corresponding to 40-320 subframes. Any vehicle can transmit twice (with 1 blind retransmission) on any two selected subframes in time domain within this period (sidelink subframes). Within every sidelink subframe, there are resource pools allocated for sidelink transmission and the vehicle dynamically selects a subset of these resource pools (Physical Resource Blocks (PRBs)) for transmission. In mode 3, the eNB controls the selection of sidelink subframes and resource pools whereas in mode 4, the vehicle autonomously select from a set of pre-configured resource pools.

Each sidelink subframe (1 ms) contains 14 OFDM symbols out of which 10 are used for carrying user data and the remaining 4 (at positions [2,5,8,11] with 0-based indexing) are used for carrying DMRS symbols. The DMRS symbols are sequences $\tilde{r}_{u,v}(n)$ that are obtained by a cyclic shift of a base sequence $r_{u,v}(n)$ according to

$$r_{u,v}(n) = e^{j\pi n a}, \quad 0 \leq n \leq M_{rs}^{RS}$$

where $M_{sc}^{RS} = mN_{sc}^{RB}$ is the length of the DMRS sequence, $m$ is the number of PRBs and $N_{sc}^{RB}$ is the number of subcarriers within one PRB (12 in case of LTE). The base sequence itself is defined as the cyclic extension of the Zadoff-Chu Sequence and is given as

$$\tilde{r}_{u,v}(n) = x_q(n \mod N_{zc}^{RS}), \quad 0 \leq n \leq M_{sc}^{RS}$$

where $x_q(n)$ is the $q_{th}$ root of Zadoff-Chu sequence and $N_{zc}^{RS}$ is the length of Zadoff-Chu sequence that is given by the largest prime number such that $N_{zc}^{RS} < M_{sc}^{RS} < 3N_{sc}^{RB}$; the base sequence is defined as the computer generated constant amplitude zero autocorrelation (CG-CAZAC) sequence.

The transmitting node can select a base sequence from a set of groups each differentiated with a hopping sequence that depends on the current subframe number and the V2X scrambling identity. In this way, the DMRS sequences are randomized for different vehicles thereby reducing inter-cell interference.

The DMRS symbols along with the data symbols are multiplexed together, modulated by Single Carrier - Frequency Division Multiple Access (SC-FDMA) and then passed through a channel. At the receiver, the received OFDM grid denoted as $Y_t$ is given as

$$Y_t = H_t X_t + N_t,$$

where $H_t$ is the channel frequency response and $N_t$ is the AWGN for symbol $t$.

As a first step in LS channel estimation, the receiver extracts the pilot symbols from their known location in the time-frequency grid and divides them with their expected value

$$\tilde{H}(i,k) = \frac{Y(i,k)}{X(i,k)} = H(i,k) + N(i,k)$$

where $\tilde{H}(i,k)$ is the LS channel estimate at pilot location $(i,k)$, $Y(i,k)$ and $X(i,k)$ are the received and sent pilot symbols at $(i,k)$ and $N(i,k)$ is the noise at $(i,k)$. It can be seen that the calculated LS estimate is noisy and hence in order to minimize the effect of noise, a 2D averaging is performed with a chosen window size. Hence, averaging the instantaneous channel estimates over the window, we have

$$\tilde{H}_{AVG}(i,k) = \frac{1}{|S|} \sum_{m \in S} \tilde{H}(i,k)(m) \approx H(i,k)$$

where $S$ is the set of pilots in the 2D window and $|S|$ is the number of pilots in $S$. The LS estimates and the averaged estimates contain the same data, apart from additive noise. Simply taking the difference between the two estimates results in a noise level value for the LS channel estimates at pilot symbol locations. This knowledge of noise can be useful to increase the performance of some receivers especially using soft demodulation techniques.

Finally, the averaged LS estimates are interpolated across the whole time-frequency grid to get the complete channel matrix $H(t)$ for the received subframe. Equalization is performed by multiplying the received grid $Y(t)$ with the complex conjugate of $H(t)$.
TABLE I: Simulation Parameters

| Parameter Group | Name     | Value |
|-----------------|----------|-------|
| High-level Parameters | TBS     | 3496  |
|                  | N_Subframes | 500   |
|                  | SNR Range  | [-2, 5] dB |
|                  | Modulation | QPSK  |
| SCI Message      | Time Gap  | 1 subframe |
|                  | Delay Profile | EVA  |
| Data Message     | MIMO     | 1X2   |
|                  | Speeds    | [100,200,300,400] kmph |
| Channel          |          |       |

\[ Y_{eq}(t) = Y(t) * H(t)^* \]

III. SIMULATION METHODOLOGY

As a proof-of-concept, we applied the ANN based channel estimation on simulated data. The simulation method is outlined in Figure 1. For the given set of parameters as outlined in Table I, we generated a set of sidelink subframes. These subframes were then converted to a time domain waveform by employing SC-FDMA and the waveform was passed through a multi-path fading channel (with EVA delay profile) to get the received grid \(Y_t\). The receiver operations consist of subframe synchronization followed by perfect and practical channel estimation that produced channel matrices (\(H_{perf}\) and \(H_{prac}\) respectively. The noisy LS estimates were obtained by dividing the received DMRS with the transmitted DMRS symbols and is linearly interpolated over each subframe to get \(Y_{noisy}\).

A. Data Generation & Preparation

For the training data, we generated a total of 500 subframe samples for SNR values ranging between \([-2, 5]\) dB hence totaling 5000 samples. This process was repeated for 4 different speeds (Table I) bringing the total number of samples to 20000. Each sample is has a shape of \((576, 14)\) corresponding to 48 PRBs in frequency domain and 14 symbols in time domain. \(Y\) also has a similar shape as \(X\).

B. DL architectures

Deep Learning (DL) belongs to a class of ML algorithms that uses multiple layers of non linear processing units stacked on top of each other. Each successive layer uses the output of the previous layer as input. Such DL architectures are especially suitable for designing auto encoders that aim to find a low-dimensional representation of its input at some intermediate layer that allows reconstruction at the output with minimal error. DL architectures can be broadly classified into two categories - CNNs which are good at finding spatial patterns in the data and RNNs which are good at finding temporal correlations.

In this work, we adopt DL architecture based on CNN and compare their performance with respect to Block Error Rate (BLER) and Error Vector Magnitude (EVM) to that of the perfect and practical channel estimators. As shown in Figure 2, the proposed model consists of 4 convolutional layers with different kernel sizes each of them followed by a batch normalization to minimize vanishing or exploding gradients. The final layer is a Dense layer followed by a reshape layer to reshape the data to have the same dimensions as the input data.

C. Training

The input to the ANN is the noisy interpolated LS channel matrix \(H_{noisy}\) and the output is the estimated channel matrix \(H_{pred}\).

\[ \hat{H}_{pred} = f(\Phi; \hat{H}_{noisy}) \]

where \(\Phi\) is the set of parameters of the ANN.

For training, we used 30% of the samples. Finally, the trained model is used to output the \(\hat{H}_{pred}\) for the whole sample set.

The loss function is the Mean Squared Error (MSE) between the estimated \(\hat{H}_{est}\) and perfect channel matrix \(H_{perf}\) and is calculated as follows

\[ MSE = \frac{1}{|\mathcal{I}|} \sum_{h \in \mathcal{H}} \left\| f(\Phi; \hat{H}_{pred}) - \hat{H}_{perf} \right\|^2 \]

For optimizing the loss, Adaptive Moment Estimation (ADAM) optimizer was used. It computes the learning rates by
calculating an exponentially decaying average of past gradients $m_t$ in addition to past squared gradients $v_t$ as follows [20]

\[
m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t
\]

\[
v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2
\]

These values are then used to update the weights according to following rule

\[
\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t} + \epsilon} m_t
\]

We trained the network for 20 epochs and used this to predict $\hat{H}_{pred}$

D. Evaluation

The predicted channel $\hat{H}_{pred}$ is then used for equalizing the received grid. The equalized grid is then subsequently decoded and compared to the input data bits to obtain the BLER. In order to quantify the performance of the practical and ANN based channel estimator, the EVM was chosen as the metric that is calculated as follows

\[
EVM = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (e_k^2 + (Q_k - \hat{Q}_k)^2)} \times 100
\]

where $e_k = (I_k - \hat{I}_k)^2 + (Q_k - \hat{Q}_k)^2$, $(I_k, Q_k)$ & $(\hat{I}_k, \hat{Q}_k)$ represent the In-phase component and the Quadrature phase component of the ideal and measured symbols respectively.

E. Results

Figure 3 shows the BLER performance comparison between the practical channel estimator and the ANN based channel estimator. It can be clearly seen that the ANN based channel estimation scheme performs on par with the LS scheme at low speeds and low SNRs. The real benefits of using ANN scheme become apparent at higher speeds and higher SNRs as the proposed scheme outperforms LS scheme by almost an order of magnitude. This is because, at higher speeds, the averaging and interpolation used in LS causes excessive information loss thereby resulting in pure noise. In contrast, ANN was better able to learn the quick channel variations in high speed scenarios. Figure 4 also shows the EVM performance between the ANN and the LS schemes. It can be seen that the EVM is almost identical for both the schemes at low speeds. At higher speeds and higher SNRs, ANN scheme shows lower EVM than the LS scheme due to the effectiveness of the channel estimation.

IV. CONCLUSIONS & FUTURE WORK

In this work, the use of DL based on CNN was investigated for the purpose of channel estimation in high mobility C-V2X scenarios. The proposed models were trained on data generated by means of simulations using the vehicular channel model with EVA delay profile. The trained models were used to output the predicted channel matrix. The BLER results show that the proposed architecture performs better than the legacy LS scheme at high speeds. Hence, given their better resilience to high channel variations in vehicular mobility scenarios, the proposed DL architecture can be used for channel estimation in C-V2X.

As future work, the following investigations can be carried out

1. The proposed model is only trained on limited channel instantiations and SNR points. The models is expected to show better performance when trained on a more extensive constellation.
2 Using Transfer learning to re-train the existing model on real-world data.
3 Modifying / adding more layers to the existing network to increase its performance.

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