Modelling and Estimation of a Vehicle-to-Vehicle Communication Channel

by

KATTA PRADEEP SHEKHAR

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CERTIFICATE

This is to certify that the report entitied **Modelling and Estimation of a Vehicle-to-Vehicle Communication Channel**, submitted by **Katta Pradeep Shekhar, EE12B032**, to the **Department of Electrical Engineering, Indian Institute of Technology Madras**, for the award of the degree of **Bachelor of Technology**, is a bona fide record of the research work carried out by him under my supervision. The contents of this project, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Dr. Arun Pachai Kannu

Assistant Professor

Department of Electrical Engineering

Indian Institute of Technology Madras

June, 2016

Abstract

Future transportation systems promise increased safety and energy efficiency. Realization of such systems will require vehicle-to-vehicle(V2V) communication technology. Herein, a geometry-based stochastic channel modeling is employed to develop a characterization of V2V channels. The resultant model exhibits sparsity and it is exploited by using compressed sensing technique to estimate the channel. Numerical simulations are used to evaluate the performance of the estimation algorithm.

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I thank my parents and friends for their continuous support and encouragement. This accomplishment would not have been possible without them.

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Abbreviations

AOA	**Angle of Arrival**
AOD	**Angle of Departure**
CS	**Compressed Sensing**
DI	**Diffuse**
GSCM	**Geometry based Stochastic Channel Model**
LOS	**Line Of Sight**
MD	**Mobile Discrete**
MSE	**Mean Squared Error**
PDF	**Probability Density Function**
RX	**Receiver**
SD	**Static Discrete**
SNR	**Signal to Noise Ratio**
TX	**Transmitter**
V2V	**Vehicle-to-Vehicle**

Chapter 1

Introduction

1.1 Overview

In recent years, vehicle-to-vehicle (V2V) wireless communications have received a lot of attention, because of its numerous applications [4]. It is central to future intelligent transportation systems. It is well-known that the design of a wireless system requires knowledge about the characteristics of the propagation channel in which the envisioned system will operate. A big challenge of realizing V2V communication is the inherent fast channel variations due to the mobility of both the transmitter and the receiver [5]. V2V channels are also highly dependent on the geometry of the road and the local physical environment.

In this work, I adopt the geometry based stochastic channel model(GSCM) proposed in [1]. GSCMs build on placing (diffuse or discrete) scatterers at random, according to certain statistical distributions, and assigning them (scattering) properties. The signal contributions from all the scatterers are then summed up at the receiver [1].

The channel model is then used to find the channel output y[n] from the discrete time input signal s[n] using the communication system model [2], which will be discussed in further chapters. A V2V channel estimation algorithm, exploiting the aforementioned channel model is proposed to estimate the channel from input and output data.

1.2 Organisation of thesis

Chapter2 describes the Geometry based stochastic model of the v2V communication channel.

Chapter3 explains the communication system model.

Chapter4 gives an implementation recipe of the channel estimation algorithm.

Chapter5 discusses the simulation results and comparisons.

Chapter6 presents the conclusions of the project.

Chapter 2

A Geometry Based Stochastic Channel Model

First, a general model outline is discussed and then each part is discussed in detail.

2.1 General Model Outline

As mentioned in the introduction, the basic idea of GSCMs is to place an ensemble of point scatterers according to a statistical distribution, assign then different channel properties, determine their respective signal contribution and finally sum up the total contribution at the receiver. Therefore, a two-dimensional geometry as in Fig. 2.1 is defined, where we distinguish between three types of point scatterers: mobile discrete, static discrete and diffuse. The V2V channel model considers four types of multi-path components (MPCs): (i) the effective line-of-sight (LOS) component, which may contain the ground reflections, (ii) discrete components generated from reflections of discrete mobile scatterers (MD), e.g., other vehicles, (iii) discrete components reflected from discrete static scatterers (SD) such as bridges, large traffic signs, etc., and (iv) diffuse components (DI). Thus, the V2V channel impulse response can be written as [6]

$$h(t,\tau) = h_{LOS}(t,\tau) + \sum_{i=1}^{N_{MD}} h_{MD,i}(t,\tau) + \sum_{i=1}^{N_{SD}} h_{SD,i}(t,\tau) + \sum_{i=1}^{N_{DI}} h_{DI,i}(t,\tau) \qquad (2.1)$$

where N_{MD} denotes the number of discrete mobile scatterers, N_{SD} is the number of discrete static scatterers and N_{DI} is the number of diffuse scatterers, respectively. Typically, N_{DI} is much larger than N_{SD} and N_{MD} [1].

The multi-path components can be modeled as

$$h_i(t,\tau) = \eta_i \delta(\tau - \tau_i) e^{-j2\pi\nu_i t} \tag{2.2}$$

where η_i is the complex channel gain, τ_i is the delay and ν_i is the doppler shift associated with path i and $\delta(t)$ is the Dirac delta function.

Hence, the position and speed of the scatterers, transmitter, and receiver determine the delay-Doppler parameters for each multi-path component(MPC), which in turn determines $h(t,\tau)$.

2.2 Scatterer Distributions

First, the number of point scatterers of each type is fixed by defining densities χ_{MD}, χ_{SD} and χ_{DI}, stating the number of scatterers per meter. Then, the y-coordinate of MD scatterers were modeled by a uniform discrete PDF, with possible outcomes equalling the number of road lanes. Their initial xcoordinates are modeled by a (continuous) uniform distribution over the length of the road strip, i.e., $x_{MD} \sim u[x_{min}, x_{max}]$. Thus, a simplified model for the distribution of discrete mobile scatterers was used; however, our generic model can easily incorporate more complicated traffic models.

The xcoordinates of static discrete scatterers as well as diffuse scatterers are also modeled by uniform distribution over the length of the road strip. To model the SD scatterers at either side of the road, the number of scatterers were split into two and separate y-coordinates for each side were derived using Gaussian distribution. Diffuse scatterers are also modeled on each side of the road strip; their y coordinates are drawn from uniform distributions, over the intervals $y_{DI_1} \sim u[y_{1,DI} - W_{DI}/2, y_{1,DI} + W_{DI}/2]$ and $y_{DI_2} \sim u[y_{2,DI} W_{DI}/2, y_{2,DI} + W_{DI}/2]$, where W_{DI} is the width of the scatterer field.

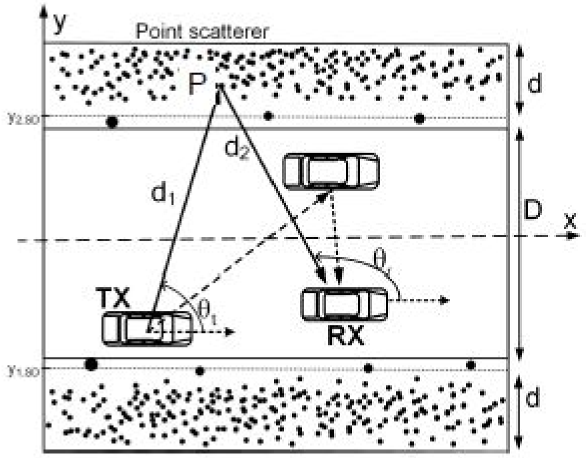

FIGURE 2.1: V2V-geometry

2.3 Scatterer Amplitudes

This section describes modelling of the complex path amplitudes of different scatterers.

2.3.1 Discrete Scatterer Amplitude

The complex path amplitude of the discrete scatterers was modeled as fading, thus representing the combined contributions of several unresolvable paths by a single process. It consists of a deterministic(distance decaying) part and a stochastic part, i.e.,

$$\eta_p(d_p) = g_{S,p} e^{j\phi_p} G_{o,p}^{1/2} (\frac{d_{ref}}{d_p})^{n_p/2} \tag{2.3}$$

where, p represents a MD/SD scatterer, $g_{S,p}$ is the real-valued, slowly varying stochastic amplitude gain of the scatterer, $G_{o,p}$ is the received power at a reference distance d_{ref}, d_p is the total distance of the path from transmitter to the receiver via scatterer and n_p is the path loss exponent (this representation is similar to the classical model for (narrowband) pathloss [7]). The phase of the complex amplitude was modeled following the classical GSCM approach of giving a random phase shift, uniform over [0,2π] [1].

2.3.2 LOS Amplitude

LOS components are also modeled as fading because of the contributions from ground reflection which cannot be resolved from the true LOS. So, it was modeled using the same model as for the discrete components.

2.3.3 Diffuse Scatterer Amplitude

The complex path amplitude of a diffuse scatterer r was modeled as in classical GCSM by

$$\eta_r = c_r G_{o,DI}^{1/2} \left(\frac{d_{ref}}{d_{T-r} * d_{r-R}}\right)^{n_{DI}/2} \tag{2.4}$$

where c_r is zero mean complex Gaussian distribution. The path loss exponent n_{DI} and the reference power $G_{o,DI}$ are the same for all diffuse scatterers.

2.4 Delay and Doppler Contributions

If vehicles are assumed to travel parallel with the x-axis, the overall Doppler shift for the path from the transmitter (at position TX) via the point scatterer (at position P) to the receiver (at position RX) can be written as [7]

$$\nu(\theta_t, \theta_r) = \frac{1}{\lambda_\nu}[(v_T - v_P)cos\theta_t + (v_R - v_P)cos\theta_r] \tag{2.5}$$

where λ_ν is the wavelength, v_T , v_P and v_R are the velocities of the transmitter, scatterer, and receiver respectively, and θ_t and θ_r are the angle of departure and arrival respectively.

The path delay due to a scatterer at point P, as shown in fig. 2.1 depends on the distances d_1 and d_2 and is given by

$$\tau = \frac{d_1 + d_2}{c_o} \tag{2.6}$$

where c_o is the propagation speed, d_1 is the distance from TX to P, and d_2 is the distance from P to RX. The path parameters θ_t, θ_r, d_1, and d_2 are easily computed from the positions of TX, P, and RX.

2.5 Simulation Recipe

The simulation procedure of the V2V GSCM can be summarized as follows:

1. Specify the physical limits of the geometry $\{x_{min}, x_{max}\}$, and determine the number of MD,SD and DI scatterers from their respective densities.
2. Specify the simulation time frame and generate coordinates to different scatterers as well as the vehicles according to section 2.2.
3. Choose the speeds of transmitter, receiver and MD scatterers.
4. For each time instant, calculate the propagation distance, AOA and AOD for the LOS path as well as the single-bounce path from TX to RX via each scatterer. Using these, calculate the delay-doppler contributions from each scatterer using (2.5) and (2.6).
5. **Delay Quantization:** As we are modelling the channel in discrete time-delay domain, specify a quantization size for delays.
6. For each time sample, sum up the contributions at the RX according to (2.1).

Chapter 3

Communication System Model

Lets consider communication between two moving vehicles as shown in Fig. 2.1. The input signal s[n] is created by randomly generating a sequence of 1s and -1s. The discrete time representation of the received signal, y[n] can be written as,

$$y[n] = \sum_{m=\infty}^{+\infty} h[n,m]s[n-m] + z[n] \tag{3.1}$$

where $h[n,m]$ is the discrete time-delay representation of the observed channel, z[n] is the complex white Gaussian noise, which is modelled using complex gaussian random variables with variance ${\sigma_z}^2$. If we assume that $h[n,m]$ is causal with maximum delay M-1, i.e., $h[n,m] = 0$ for $m \geq M$ and $m < 0$, then we can write

$$y[n] = \sum_{m=0}^{M-1} \Big(\sum_{k=-K}^{K} H[k,m]e^{j\frac{2\pi nk}{2K+1}} \Big) s[n-m] + z[n] \tag{3.2}$$

$$for\ n = 0, 1, ..., N_r - 1.$$

where $2K + 1 \geq N_r$ and

$$H[k,m] = \frac{1}{2K+1} \sum_{n=0}^{N_r-1} h[n,m]e^{j\frac{2\pi nk}{2K+1}},\ for\ |k| \leq K \tag{3.3}$$

is the discrete delay-Doppler spreading function of the channel. Here N_r denotes the total number of received signal samples used for the channel estimation.

3.1 Matrix notation

The channel in (3.3) can be represented for $k \in K$ and $m \in M$ by the vector $x \in C^N$, where $N = |K||M| = (2K+1)M$, $K = \{0, \pm 1, \pm 2, ..., \pm K\}$ and $M = \{0, 1, ..., M-1\}$, as

$$\mathbf{x} = \text{vec}\begin{bmatrix} H[-K,0] & & H[-K,M-1] \\ \vdots & \dots & \vdots \\ H[K,0] & \cdots & H[K,M-1] \end{bmatrix}$$

where vec(H) is the vector formed by stacking the columns of H on the top of each other.

Consider that the source vehicle transmits a sequence of $N_r + M - 1$ pilots, $s[n]$, for $n = -(M-1), -(M-2), ..., N_r - 1$, over the channel. Then the output vector has N_r samples in a column vector.

$$y = [y[0], y[1], ..., y[N_r - 1]]^T \tag{3.4}$$

Using (3.2), we have the following matrix representation:

$$y = Sx + z, \tag{3.5}$$

where $z \sim N(0, {\sigma_z}^2 I_{N_r})$ is a Gaussian noise vector and S is a $N_r \times N$ block data matrix of the form

$$S = [S_0, ..., S_{M-1}], \tag{3.6}$$

where each block $S_m \in C^{N_r \times (2K+1)}$ is of the form

$$S_m = diag\{s[-m], ..., s[N_r - m - 1]\}\Omega, \tag{3.7}$$

for m=0,1,....,M-1, and $\Omega \in C^{N_r \times (2K+1)}$ is a Vandermonde matrix, $\Omega[i,j] = exp(j2\pi/(2K+1))^{i(j-K)}$, where $i = 0, 1, ..., N_r - 1$ and $j = 0, 1, ..., 2K$ [2].

Chapter 4

Channel Estimation

In the earlier chapters, we have discussed modelling of a V2V communication channel. In this chapter, we discuss compressed sensing techniques to estimate the channel from input and output data derived using (3.5).

4.1 Sparsity of the channel

Mathematically, sparsity refers to having very few non-zero contributions when expressed in a conventional basis. To analyse the sparsity of the channel, the delay doppler contributions from all the scatterers are plotted as shown in Fig. 4.1.

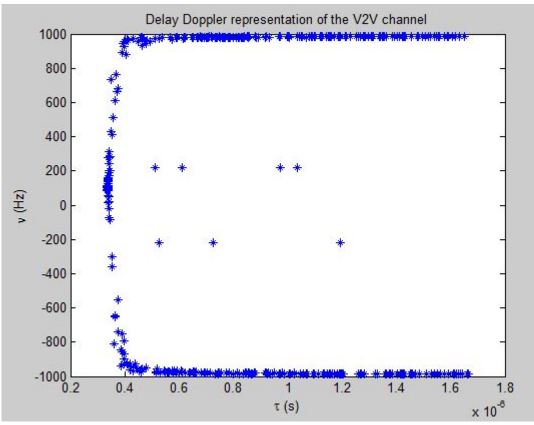

FIGURE 4.1: Delay-Doppler Domain representation of the V2V channel

We can see from the plot, that the scatterer contributions are confined to a **"U"** shaped region in the delay-doppler domain. So, the channel in our discussion is sparse and we can use "Compressed Sensing" techniques to estimate it.

4.2 Channel Estimation using Compressed Sensing

Consider the Classical linear measurement model:

$$y = S * x + z \tag{4.1}$$

where S $\in$ $C^{N_r \times N}$ is a known matrix derived using (3.6), x $\in$ $C^{N \times 1}$ is the unknown vector to be reconstructed, z is the complex gaussian noise with variance σ_z^2 and y is a known vector representing the received samples derived using (3.5).

One of the central tenets of CS theory is that if x is sparse (as in our case), then a relatively small number of appropriately designed measurement vectors can capture most of the salient information. [3]

To enforce the sparsity constraint when solving for the system of linear equations, L^1 minimization was used.

The channel vector x can be obtained as a solution to the following optimization problem:

$$\begin{aligned} &minimize\ ||x||_1 \\ &subject\ to\ ||y - S * x||_2 \leq \delta \end{aligned} \tag{4.2}$$

Chapter 5

Simulation Results

In this chapter, we discuss the performance of our estimation algorithm by looking at the variation of mean square error with changing SNR. We shall also look at some of the simulation results.

5.1 GSCM

To simulate the channel, a geometry of length 500m having 4 lanes, road width of 18m, diffuse strip of width 5m on either side of the road is considered. The initial locations of the TX and RX vehicles are chosen in this geometry with distance of 100m between them. The speeds of TX and RX vehicles are chosen to be 100 km/h and 80 km/h respectively. It is assumed that the number of MD scatterers $N_{MD} = 10$, the number of SD scatterers $N_{SD} = 10$ and the number of DI scatterers $N_{DI} = 400$; the velocities of MD scatterers were chosen randomly from the interval [60,160] (km/h) [2]. The positions of scatterers were determined based on our discussions from section 2.2.

The statistical parameter values for different scatterers are selected as in Table I of [1], which are determined from experimental measurements. The scatterer amplitudes were randomly drawn from zero mean, complex Gaussian distributions. Furthermore, frequency of operation is 5.8 GHz, T_s= 1ns, N_r = 100, M = 180 and K = 50. The discrete time-delay impulse response of the V2V communication channel simulated using the GSCM discussed in chapter 2 is as shown in Fig 5.1.

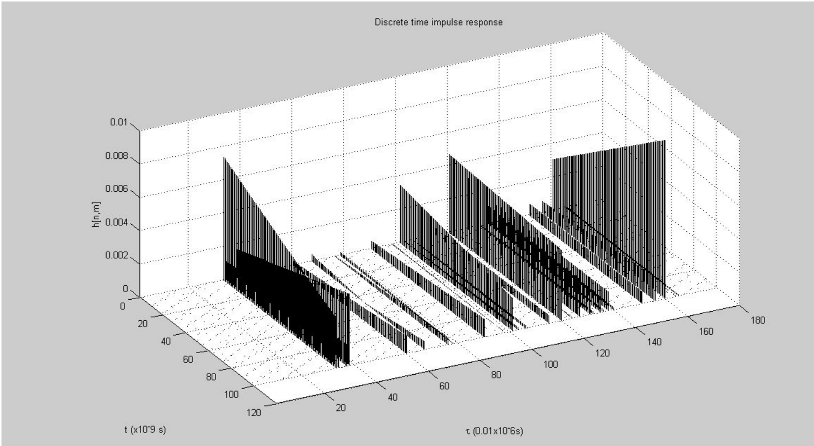

FIGURE 5.1: Time varying impulse response

5.2 Input and Output of the Channel

The input signal s[n] is modeled by randomly generating $N_r + M - 1$ samples of 1s and -1s. The "x" vector representing our time varying channel is found according to section 3.1. The output vector containing N_r samples is then generated according to (3.5).

Fig. 5.2 depicts the input and Fig. 5.3 is the plot showing real part of the output data of our proposed communication system model.

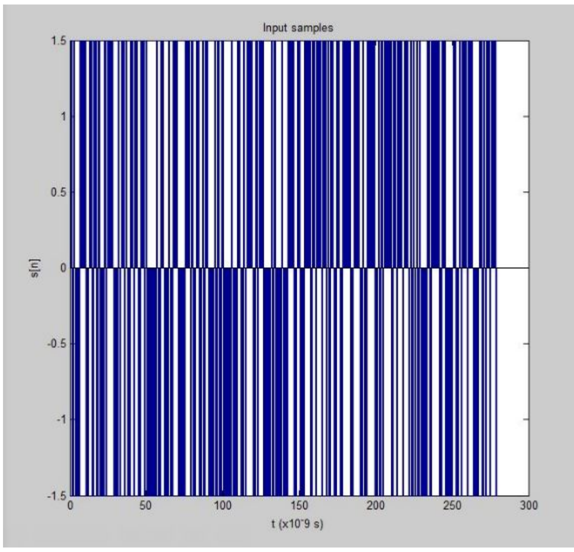

FIGURE 5.2: Input samples

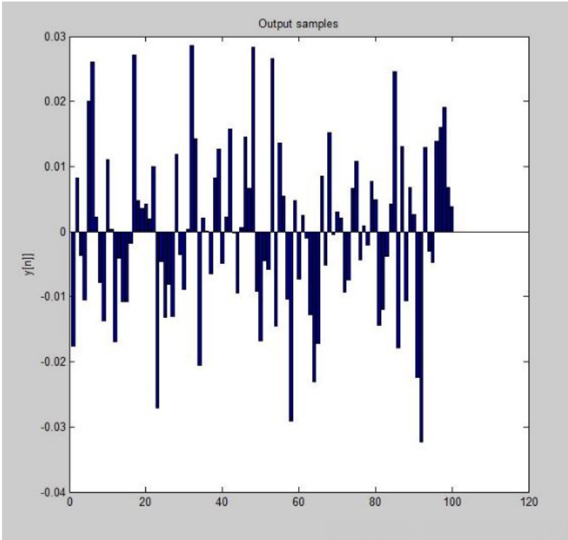

FIGURE 5.3: Output samples

5.3 Estimated Channel

Once the input and output data has been simulated, the channel vector x is estimated using the CS technique discussed in section 4.2. The figures 5.4 and 5.5 represent the simulated and estimated **"x"** vectors respectively.

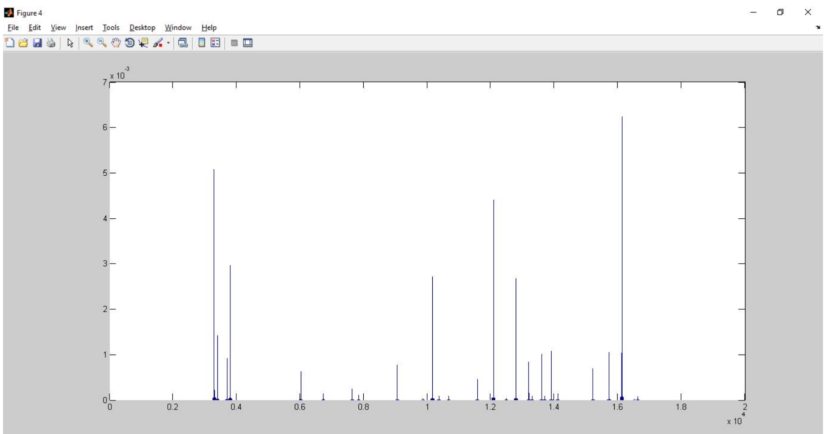

FIGURE 5.4: Simulated "x" vector

5.3.1 Mean Squared Error

The Mean squared error(MSE) between the simulated and estimated x vectors is defined as:

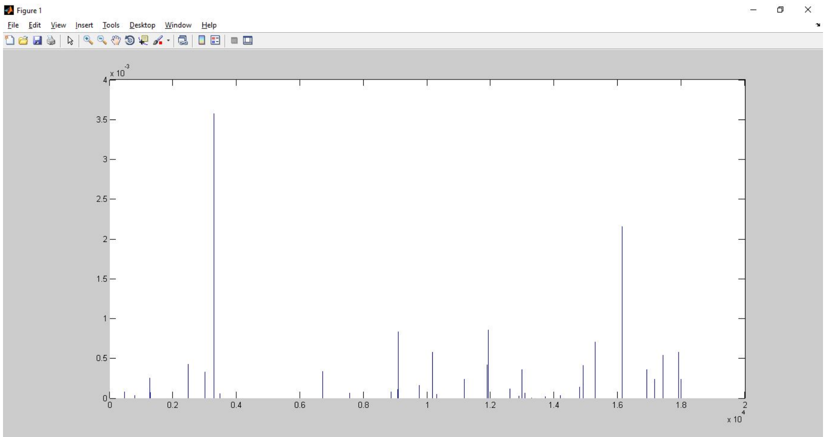

FIGURE 5.5: Estimated "x" vector

$$MSE = ||\hat{x} - x||_2 \tag{5.1}$$

where $\hat{x}$ is the estimated channel vector and x is the simulated channel vector.

As our model is not completely deterministic, MSE was calculated for 100 different pairs of randomly generated input and noise vectors and the average of these 100 values is considered as MSE.

The SNR at the receiver is varied by changing the noise variance and MSE is calculated for different levels of SNR. Fig. 5.6 shows the variation of MSE with increasing SNR.

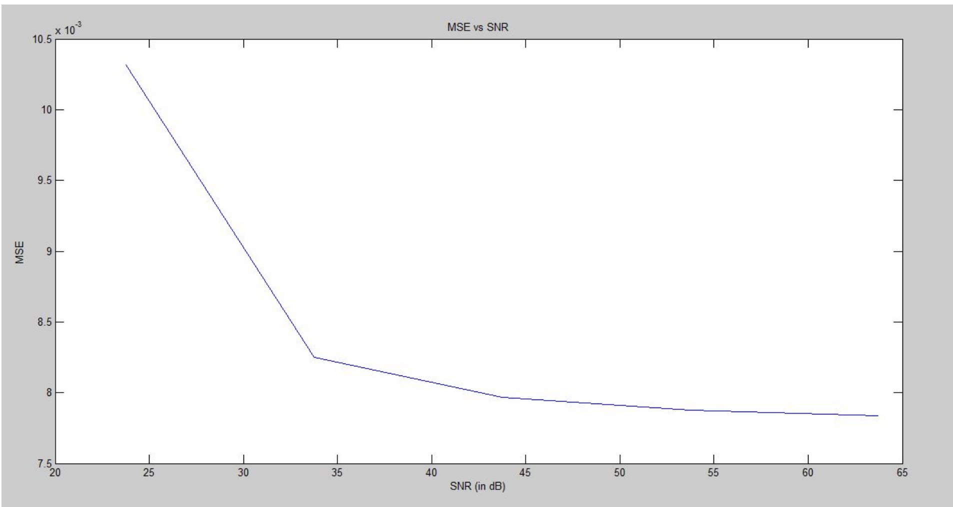

FIGURE 5.6: MSE v.s SNR

Chapter 6

Conclusions

The key aspects of this project are:

1. A classical GSCM has been used to simulate a V2V communication channel.
2. The communication system model proposed in [2] has been used to find the output data of such a channel.
3. A comprehensive analysis of V2V channels in the delay-Doppler domain has been done to exploit its sparsity structure.
4. A channel estimation algorithm using compressed sensing technique was exploited.
5. The performance of the estimation technique was evaluated by calculating the Mean Squared Error (MSE) between the estimated and simulated channel vectors.
6. MSE is found to be decreasing with increasing SNR.

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