



Bachelor Term Project

Channel Estimation for Passive Intelligent Surface aided Wireless Communication

Adit Jain

180102003

BTech, Electronics and Communication Engineering

adit18@iitg.ac.in

Under the Supervision of Dr Salil Kashyap

DEPARTMENT OF ELECTRONICS AND ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY, GUWAHATI

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Abstract

Wireless Communication is ever improving with the 5G based wireless communication being now being deployed in a lot many geographies. With the advent of beamforming technology and MIMO based communication, concerns over power consumption, security and logistical issues are bound to be raised. Many solutions have come forward for what is labelled as “5G and beyond” stack, one such solution is the use of reflecting surfaces which have reflecting elements which can inflict a phase and magnitude shift on the incoming wave and reflect it without the use of any active components.

Passive Intelligent Surfaces (PIS) or Intelligent Reflecting Surfaces (IRS) as they are sometimes called are an up and coming advancement to the ever improving field of wireless communication. PIS have a wide variety of applications including but not limited to unclogging dead zones, enhancing physical layer security and enhancing the power of the received signal. There are a wide variety of problems related to the development, deployment and operation of such a surface but this thesis concerns with the specific class of problems related to Channel Estimation for the applications related to Information Transfer, Energy Transfer or both simultaneously. Optimally estimating the channel helps in reducing training overhead, maximizing received power and reducing the variance in estimating the transmitted information among other tasks. To be very specific presently, this thesis looks into how the reflecting elements can be turned on during the training phase to optimally estimate the channel coefficients.

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1 Introduction

5G and beyond networks come with more demands than their predecessor, like improving energy efficiency, decreasing monetary costs, higher reliability and dominieeringly lower latency. However, emerging solutions to 5G services (e.g. ultra-reliable and low latency communication (URLLC)) include an increasing number of active nodes, packing more antennas and migrating to higher frequencies involves increasing energy, hardware and cost requirements. Hence this need for cheaper energy-efficient smart solutions has led to the conceptualization of Passive Intelligent Surfaces(PISs) (also known as Intelligent Reflecting Surfaces (IRSs)). These are surfaces (not necessarily flat) which reflect signals from base station to the user and vice-versa. In addition to reflecting they are also capable of changing the phase and magnitude of the signal and are configurable by a controller.

Formally, PIS is a re-configurable environment for Beyond 5G wireless communication systems constituting passive elements which reflect incoming signals and additionally inflict a controllable phase and magnitude change to them [1].

PIS reflection surface is realizable using the existing programmable meta surfaces [2]. These reflection elements are tuned by the help of a controller connected to the base station, and Micro Electro Mechanical Switches (MEMS) are used to control the reflection coefficients. This thesis does not delve into the physical implementation any more than this but details can be found in [3].

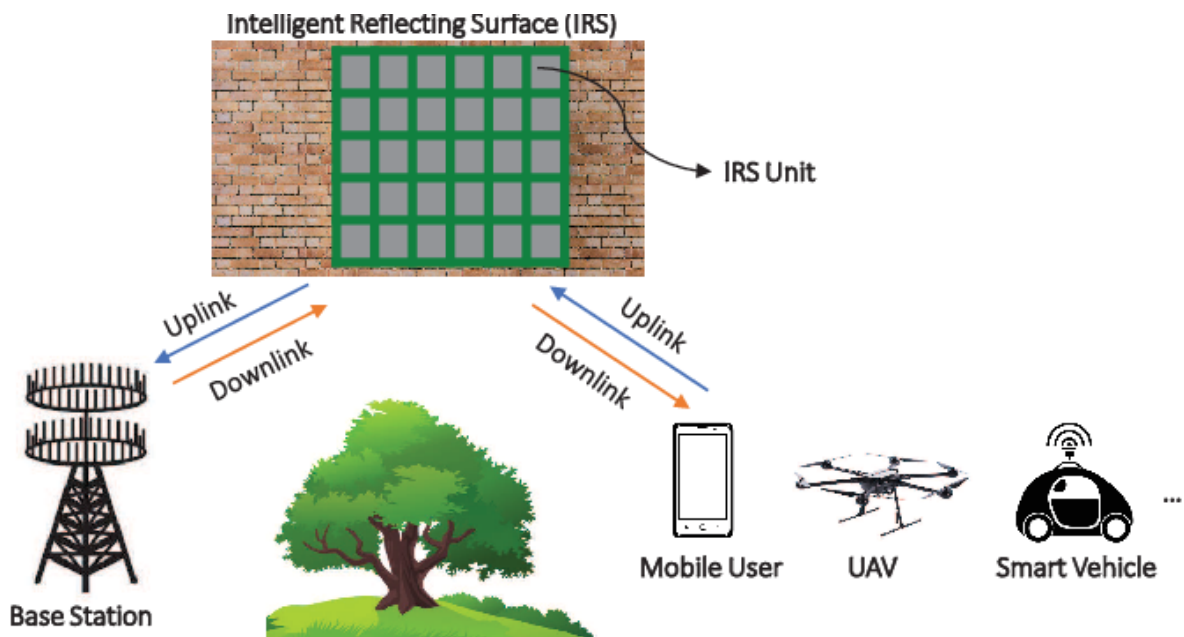


Figure 1: Basic setup of how Passive Intelligent Surfaces or Intelligent Reflecting Surfaces are deployed and work. Image Credits: Figure 1 of [4]

1.1 Advantage and Use cases of PIS

A lot of applications and use cases have been proposed for PIS, some of them include:

- *Unlocking a dead zone* which would be otherwise be unreachable by direct LoS communication. PIS can be placed at a suitable location to reflect the signal and indirectly send it to the Access Point.
- *Improving Physical Layer Security* by making the phase shift of the reflected wave such that it destructively interferes with the direct wave. This can help block signals to locations other than the intended one hence eliminating eavesdropper to intercept otherwise secure communication.
- *Increasing Received Power* and hence the energy efficiency of the system using the reflection elements to constructively add up at the access point.
- *Reducing power consumption* by using passive elements to improve communication rather than active RF chains whose power consumption increase with increasing number of chains.
- *Enabling massive Device to Device (D2D) and Simultaneous Wireless Information and Power Transfer (SWIPT) communication.*

1.2 Fundamentals of IRS Signal and Channel Model

In this work the focus is on a point to point communication system where an IRS comprising of N reflecting (passive) elements is used to assist wireless communication between a transmitting base station and a receiver. Though the simulations are based on a multiple antenna basestation, a single antenna base station and access point is considered for illustrating the signal model. The communication system is considered to be narrow band with f_c as the carrier frequency and B as the bandwidth.

Let $x(t)$ denote the equivalent complex-valued baseband transmitted signal. For a single reflecting element i (where $i \in \{1, 2, \dots, N\}$) the attenuation and phase shift induced by the IRS element can be respectively denoted as β_i and θ_i , where $\beta_i \in [0, 1]$ and $\theta_i \in [0, 2\pi)$. But realizing phase shift continuously is impractical and hence L different quantization levels are considered and therefore for the case of uniform quantization: $\theta_i \in \{0, 2\pi/L, \dots, (L-1)2\pi/L, 2\pi\}$ Taking h_i as the direct channel coefficient between the transmitter and the i^{th} reflecting element and g_i as the direct channel coefficient between the i^{th} reflecting element and the receiver. It can be shown that the received symbol, $y_i(t)$ at the receiver reflected from the i^{th} element is given by:

$$y_i(t) = \beta_i e^{j\theta_i} h_i^* g_i x(t) \quad (1)$$

Or in other words, the symbol $x(t)$ seems to be passed through a *cascaded* channel comprising of three separate channels: a) Channel between transmitter and reflecting element, b) Reflection by the element (which simulates as a channel itself) and c) Channel between reflection element and the receiver.

This single reflection element model can be extended to the N reflection elements. The received signal $y(t)$ will be the sum of the received signal from the N reflecting elements (ignoring the direct channel for now). Therefore:

$$y(t) = \sum_{i=0}^N \beta_i e^{j\theta_i} h_i^* g_i x(t) = \mathbf{h}^H \mathbf{\Theta} \mathbf{g} x(t) \quad (2)$$

Accounting for noise the equation 2 becomes:

$$y(t) = \mathbf{h}^H \mathbf{\Theta} \mathbf{g} x(t) + n(t) \quad (3)$$

where $\mathbf{h}^H = [h_1^*, \dots, h_N^*]$, $\mathbf{g} = [g_1, \dots, g_N]^T$, and $\mathbf{\Theta} = \text{diag}(\beta_1 e^{j\theta_1}, \dots, \beta_N e^{j\theta_N})$. Extending equation 3 for T training symbols x_t for $t \in [1, 2, \dots, T]$, $\mathbf{X} = [x_1, x_2, \dots, x_T]^T$ and let \mathbf{Y} be the received signal.

$$\mathbf{Y} = \text{diag}(\mathbf{X}) \mathbf{\Phi} \mathbf{H} + \mathbf{N} \quad (4)$$

where $\mathbf{\Phi}$ is the *reflection coefficient matrix* whose rows denote the different training sequence time-steps and the columns are the different reflection elements¹.

$\mathbf{H} = [h_d, h_1^* g_1, h_2^* g_2, \dots, h_N^* g_N]^T$ is the channel coefficient vector and finally \mathbf{N} is the AWGN $T \times 1$ noise vector for the different training time-steps.

Details and derivations of equation 1 and 2 can be found in [5] and [6].

1.3 Types of PIS

- Semi Passive PIS: In addition to the passive reflecting elements the PIS surface may be equipped with some active sensing devices equipped with receiver RF chains. These active devices are used to estimate the channels during the training period.
- Passive IRS: These are simply the PIS surfaces without any active devices. Channel estimation for these kind of surfaces can only be done for the cascaded channel of BS-PIS-User and not the individual channel. The elements can be turned on and off accordingly to estimate the channel. But this kind of PIS is much cheaper and energy efficient than the Semi Passive counterpart as it does not involve any active components such as radio frequency chains (RF chains).

1.4 Focus and Contributions for this phase

Extensive literature review has been undertaken to understand the fundamental of wireless communication, PIS, channel estimation and other related areas. For the purpose of this thesis problems related to channel estimation in PIS have been identified and studied upon.

To understand the impact of channel estimation and how channel estimation is undertaken in a PIS based set-up, this thesis simulates reference [7].

A better understanding was gained on how the way these reflecting elements are activated impacts the mean square error for channel estimation.

A Hadamard matrix based activation pattern is also proposed that helps achieve a better trade-off between complexity and performance in terms of mean square error.

¹The first column is the direct channel between the BS and AP.

2 Literature review on Channel Estimation

This thesis is mainly concerned with the problem of channel estimation in Passive IRS. As discussed in the previous section the cascaded channel between base Station PIS and the user/sensor can be modelled with the help of equation 2. To effectively communicate in a given time-frame the knowledge of channel coefficients \mathbf{h}^H and \mathbf{g} is necessary for equalization and demodulation. An important point is, the individual channels between BS-PIS and PIS-User(/Sensor) can not be estimated and for the simple reason that there are no active elements in the completely passive realization of a PIS. And so only the cascaded channel can be estimated but it has its own set of problems.

2.1 Problems of Estimating the Channel in PIS

Although it is not much different that the direct channel between BS-AP the reflection element's coefficient $\beta_i e^{j\theta_i}$ adds a phase shift as well as a attenuation to what might otherwise be another tap to the channel. Estimating the channel requires the cascaded channel to be estimated for all the N reflecting elements plus the direct channel. Estimating the direct channel is fairly easy and can be done by turning all the reflection elements OFF ($\beta_k = 0 \forall k \in \{1, \dots, N\}$). To estimate the cascaded channels, different patterns of turning the reflection elements can be used as will be seen in the next sub-section. But before moving ahead, an important point to keep in mind is the trade-off between training overhead associated with the channel estimation and the variance of the estimates of the channel coefficients used. This trade-off helps prioritize one technique of channel estimation over other.

There has been a lot of recent work on channel estimation for PIS-aided wireless communication, [8], [9], [7], [10] being examples. While some focus on how the training signals can be chosen [8], others [7] focus more on how the elements can be turned off and on optimally. This research focuses more on the latter.

2.2 Reflection Pattern and Estimation

To estimate the N cascaded PIS channels (one for each reflecting element) ², T training symbols need to be sent with different combinations of IRS reflection coefficients being present so as to completely estimate the cascaded channels.

Once all the training signals are received, the Least-Square estimator or the minimum variance estimator is used to get the estimates of the channel coefficients. In equation 4 let $\mathbf{V} = \text{diag}(\mathbf{X})\Phi$ and \mathbf{Y}_r be the received signal. Then using the MVU estimator, the

²The discussion so far has assumed that the reflecting elements have independently chosen reflection coefficients but these elements can be grouped so that a smaller number of channels has to be estimated and reflection coefficients calculated for. This doesn't change the results as only the value of N reduces but the model remains the same. See [11] for more details.

channel coefficient estimates H_{est} and the co-variance matrix $\mathbf{C}_{\mathbf{H}_{est}}$ for the estimates are given by:

$$\mathbf{H}_{est} = \begin{bmatrix} h_d \\ h_1^* g_1 \\ \vdots \\ h_N^* g_N \end{bmatrix} = \underset{\mathbf{H}}{\operatorname{argmin}} \|\mathbf{V}\mathbf{H} - \mathbf{Y}_r\|_2^2 = (\mathbf{V}^H \mathbf{V})^{-1} \mathbf{V}^H \mathbf{Y}_r \quad (5)$$

$$\mathbf{C}_{\mathbf{H}_{est}} = \sigma^2 (\mathbf{V}^H \mathbf{V})^{-1} \quad (6)$$

where σ is the noise variance.

2.3 Optimizing Variance of Channel Coefficients Estimates

There can be different parameters that can be used to frame the optimization problem, one of them being the mean square error of the estimates others can be the length of training sequence required or the computation overhead. Here the focus is on optimizing the MSE or the sum of the trace of the co-variance matrix of the estimator.

The optimization problem can be framed as :

minimize $\mathbf{C}_{\mathbf{H}_{est}}$

s.t.

$$\mathbf{C}_{\mathbf{H}_{est}} = \sigma^2 (\mathbf{V}^H \mathbf{V})^{-1} = \sigma^2 (\Phi^H \Phi)^{-1}, \quad \Phi \in \mathbb{C}^{TxN+1}$$

$$[\Phi]_{t,1} = 1 \text{ for } t \in [1, \dots, T]$$

$$[\Phi]_{t,k} = \beta_{t,n} e^{j\theta_{t,n}} \text{ for } t \in [1, \dots, T] \text{ and } n \in [1, \dots, N]$$

where $\beta_{t,n}$ and $\theta_{t,n}$ are the reflection coefficients for the n^{th} element for the t^{th} training symbol. The co-variance matrix described in this problem is same as the one described earlier.

Since the MVU estimator attains the CLRB for this linear model, lower bound is obtained if $\Phi^H \Phi$ is diagonal [7] and this will be attained if $\operatorname{tr}(\Phi^H \Phi)$ is maximum.

$$\operatorname{tr}(\Phi^H \Phi) = \sum_1^{N+1} \sum_1^T |[\Phi]_{t,k}|^2 \leq (N+1)T$$

Described below are the three matrices tried with DFT matrix having theoretical basis for achieving the CLRB for the MVU estimator. The first technique (On-Off Method) is the most basic one however as simulations show does sub-par with respect to the MSE. It is also important to note that any matrix should be non-singular or all rows of the matrix should be linearly independent.

2.3.1 ON OFF based Method

In this technique only one of the reflecting element is turned on for a symbol and all other elements are turned off. The reflection matrix Φ for this technique looks like:

$$\Phi_{ON-OFF} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 0 & \dots & 1 \end{bmatrix}$$

Note that the first column denotes the direct channel (which is always on) , the second column denotes the first reflecting element and so on. Similarly, the first row denotes the PIS element reflection coefficients for the first training symbol and so on. One additional requirement to this method is that length of training sequence (T) should be equal to number of reflecting elements plus a direct channel ($K + 1$)

2.3.2 DFT Matrix

Here the rows of a DFT matrix are dictate the patterns of the reflection coefficients. It follows that the amplitude attenuation ($\beta_{t,n}$) remains one throughout and only the phase shift coefficients $\theta_{t,n}$ changes according to the training period and the reflection element. Here, the reflection matrix Φ is:

$$\Phi_{DFT} = \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & e^{-\frac{2\pi j}{T}} & e^{-\frac{2\pi 2j}{T}} & \dots & e^{-\frac{2\pi Nj}{T}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & e^{-\frac{2\pi Tj}{T}} & e^{-\frac{2\pi 2Tj}{T}} & \dots & e^{-\frac{2\pi NTj}{T}} \end{bmatrix}$$

Since there is no constraint on T , the length of training signal can be increased to decrease the MSE further.

2.3.3 Hadamard Matrix

One more matrix that can be considered is the Hadamard Matrix, which is a square matrix with 2^k ($k \in \mathbb{N}$) rows. The truncated TxN+1 matrix of this is considered to mimic the patterns of the reflections coefficients of the IRS [12]. An example of this matrix for 4 training signals and 2 reflection elements would look like:

$$\Phi_{had} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & -1 \\ 1 & -1 & -1 \end{bmatrix}$$

3 Simulations and Numerical Results

The simulations carried out record the Mean Squared Error by varying the Number of Antennas at the BS, the number of reflecting elements and the input signal power. Increasing all of which decreases the MSE of the Channel coefficients estimates. The results are plotted in figures 2,3 and 4.

3.1 Parameters

The different parameters and assumptions for conducting the simulations are as follows unless varied or constrained upon:

- Noise is AWGN with power 0.01
- Number of antennas at BS: 10
- Power Scaling Factor of the signal: 10
- Number of Groups/Elements: 10
- Length of Training Signal: 16
- Number of Simulations: 1000

3.2 Results

As can be seen from the figures 2,3 and 4, the DFT matrix reflection patterns outperform the other technique when the estimate MSE are concerned especially the traditional ON OFF based technique by a factor of 10 . The Hadamard matrix based approach is sort of in between the other two, it is simple to implement and needs only 2 phase shift possible on the PIS elements for the training phase but it is more erroneous than the more complicated and implementation-ally tough DFT based approach.

An important point to be noted is that the trace of both the Hadamard Matrix and the DFT matrix attain the CLRB described earlier. But practically the DFT matrix based approach outperforms the Hadamard matrix reasons to which need to be investigated.

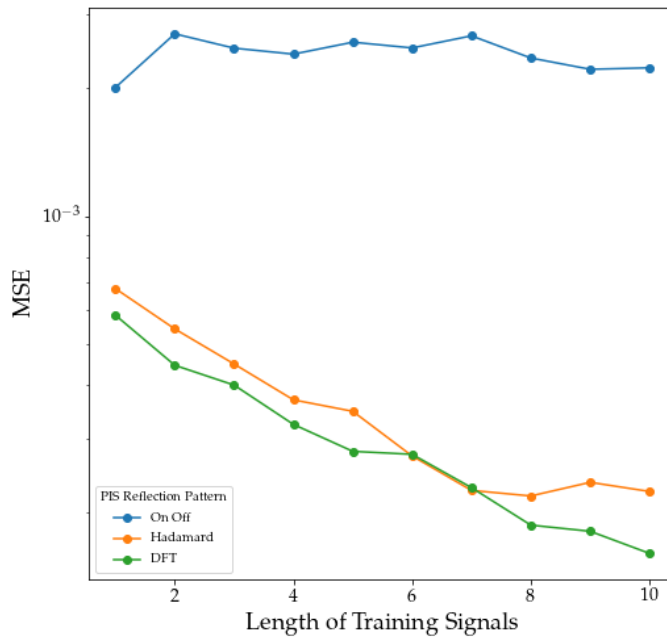


Figure 2: Impact of the pilot sequence length on mean square error for three different activation patterns for the reflection elements of the PIS

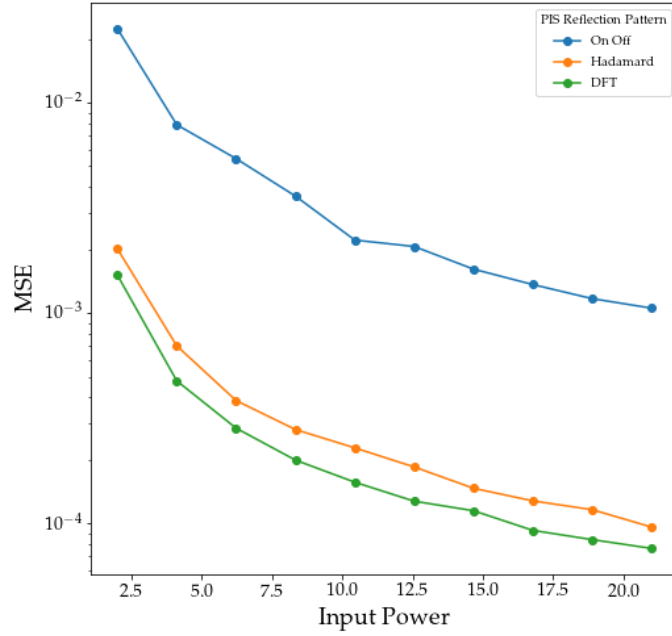


Figure 3: Impact of transmit power on mean square error for three different activation patterns for the reflection elements of the PIS

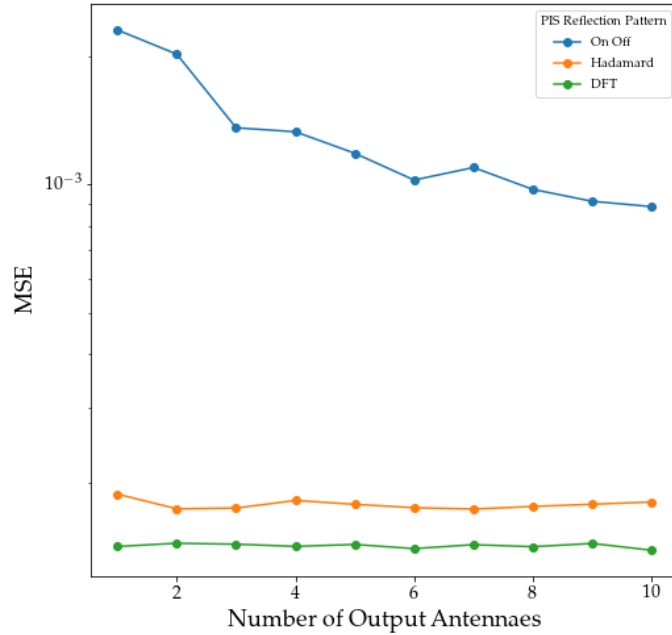


Figure 4: Impact of number of active antennas on the mean square error for three different activation patterns for the reflection elements of the PIS

4 Conclusion and Future Work

There's a lot of scope using the preliminary research that has been undertaken. Some areas/problems that can be explored including but not limited to:

1. Although the DFT matrix and its permutations is mathematically proven to give the minimum MSE it does need a lot of phase shift quantized levels of reflection elements. So are there other reflection schemes that can achieve better?
2. Here all the cascaded channels and the direct channel are estimated, this kind of estimation proves to be great for information transfer, but research [13] shows full CSI might not be needed for Energy Transfer applications. So can imperfect CSI using grouped reflection elements help improve energy efficiency but keep the number of reflection elements to a minimum.
3. The reflection coefficients of the PIS elements also constitute the cascade channels and the focus in this thesis was to find out the channel coefficients from BS to PIS and PIS to AP given the reflection coefficients that are chosen. Now once the channel coefficients are known can the reflection coefficients be optimally chosen to constructively/destructively add the reflected waves at the user end?
4. Modeling, analysis and performance evaluation of an PIS based SWIPT with estimated channel coefficients where the objective would be to maximize the data rate that can be achieved by a sensor with decoding capabilities while guaranteeing a certain energy being harvested by sensors with energy harvesting capability

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