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A Review of MMSE Based SMP Algorithm for Channel Estimation in MIMO Systems

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ABSTRACT - ***Channel estimation scheme based on minimum mean square estimation (MMSE) and sparse message passing (SMP) has been proposed .This can yield better performance since it can capture the inherent sparseness of the millimeter wave (mm wave) channel. MMSE-SMP algorithm reduces the pathloss,fading, shadowing effects, co-channel interference, channeluncertainitiy. This effects can be reduced by increasing the number of transmit antennas and receive antennas. Also, MMSE-SMP does not require the prior knowledge of the channel distribution and provide better performance. Even with less number of transmit and receive antennas itself can provide better performance.***

Index Terms: Sparse Message passing (SMP), Minimum Mean Square Estimation (MMSE), Millimeter wave, Iterative Channel Estimation.

I. INTRODUCTION

The increase in the number of mobile data growth and the number of users of smartphones had led many challenges for wireless service to overcome the global band width shortage.Millimeter-wave (mmWave) (30–300 GHz) multiple-input multiple-output (MIMO) with large antenna array has been considered a promising solution to meet the one thousand times increase in data traffic predicted for future 5G wireless communications.MmWave can provide nearly 2 GHz bandwidth is much larger than the 20 MHz bandwidth in current 4G wireless communications without carrier aggregation. On the other hand, the short wavelengths associated with mmWave frequencies enable a large antenna array to be packed in a small physical size means MIMO with a large antenna array is possible at mmWave frequencies to effectively compensate the high path loss induced by high frequencies and considerably improve the spectrum efficiency.One challenging problem is that each antenna in MIMO systems usually requires one dedicated radio-frequency (RF) chain, including digital-to-analog converters (DACs), mixers. This will result in unaffordable hardware cost and power consumption in mmWave MIMO systems, as the number of antennas is huge and the power consumption of the RF chain is high. Therefore, the large number of RF chains with prohibitively high power consumption is a bottleneck for mmWave MIMO with large antenna array in practice.

When a signal is transmitted it passes through a channel. Therefore there is a channel effect at the receiver end. So there is a need of estimating the channel at the receiver side for proper reception of the signal. There are several ways to estimate the channel at the receiver end. LSE estimation. LSE-SMP and MMSE-SMP estimation are the some of the algorithms which are proposed for the estimation. This will provide better performance since the BER is very low.

II. OVERVIEW OF CHANNEL ESTIMATION

Multiple antennas at transmit and receive side (multiple-input multiple-output (MIMO)) can result in a significant capacity increase. This is due to two effects: (i)robustness against fading of the channel between one transmit and a receive antenna, and (ii) space-time coding, i.e., the parallel transmission of information via multiple transmit antennas. However, this capacity increase was based on an important assumption: all channels between the transmit antennas and the receive antennas are accurately known. The wireless channel is highly complex. Hence the channel should be estimated.Pathloss, fading are some of the challenges which are facing in signal transmission and reception.Inorder to reduce these effects we propose MMSE-SMP algorithm which provide the better performance.

III. METHODS

The main interest of channel estimation is to estimate the effect of channel at the receiver end for better reception of the signal. In terms of research objectives, previous area can be divided into three categories. The first category which require prior knowledge of the channel distribution, second category which require partial prior knowledge of the channel distribution and the third category which does not require the prior knowledge of the channel distribution.

3.1 Channel Estimation with Prior Knowledge of Channel Distribution

Message passing algorithms for compressed sensing[1] proposed a new class of low complexity iterative thresholding algorithm for the reconstruction of sparse signals which is referred to as approximate message passing(AMP). AMP is justified by applying sum product belief propagation for a suitable joint distribution over the variables. Compressed sensing techniques is use to recover the signal accurately by under sampling the signals [2]. Comparing with the traditional sampling theory requires expensive reconstruction schemes.

3.2Channel Estimation with Partial Prior Knowledge of Channel Distribution

In the work [3] channel estimation for the equalization is a problem in signal processing. Minimal prior information of the channel is required but the impulse response is too long and the accuracy is no longer better and computation is complex. This can be done by two stages. In first stage the proposed a detection problem to determine non zero taps into on-off keying and in second stage the channel estimate is refined once the location of nonzero taps have determined.Channel Estimation and Hybrid Precoding for Millimeter Wave Cellular Systems [4] employ directional beam forming with large antenna arras at both transmitter and receiver. Due to high cost and power consumption mm wave precoding was divided among both analog and digital domain. It exploits the poor scattering nature of the channel. Orthogonal matching pursuit(OMP) [5] they proposed an algorithm for the recovery of high dimensional sparse signal based on a number of linear measurements. OMP is an iterative algorithm such that under mutual incoherence and minimum magnitude of nonzero components of signals the support of the signal recovered with high probability.

3.3 Channel Estimation without Prior Knowledge of Channel Distribution

Channel estimation by LSE [6]do not need a probabilistic assumption but only a deterministic signal model.It has a broader range of applications.Least squares is unbiased. To keep the variance low, the number of observations must be greater than the number of variables to estimate. In the work [7] reduces the severe pathloss by increasing the number of transmit antennas and receive antennas. BER is very low when performing the effect of iterations and effect of sparsity ratio which in turn provide better performance. This can leverages both LSE and SMP algorithms.In this work [8] they proposed how the sparsity may obtained in linear models. This can be done b prior learning with respect to marginal likelihood of the data. Expectation maximization Bernoulli guassian approximation [9] approximate message passing (AMP) algorithm is computationally an attractive solution for least square problem in compressed sensing. For making better performance, they applied expectation maximization as Bayesian variation of AMP.

IV. CONCLUSION

We have presented a sparse channel estimation algorithm(MMSE-SMP) for mm wave MIMO systems which leverages both SMP and MMSE algorithms. It can capture the sparseness of the system to provide better performance. It allows for low BER and SNR. Pathloss one of the main challenge in the mm wave MIMO can be reduced by number of transmit and receive antennas and sparse nature of the channel.

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