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CHANNEL PREDICTION TECHNIQUE IN MIMO OFDM SYSTEMS

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Abstract: Channel prediction is one of the most important techniques in MIMO OFDM systems. Performance degradation occurs due to the spatial & temporal correlation of transmitting and receiving antennas. Channel feedback delay will cause the degradation in system performance. In this work, Auto regressive model is used to predict channel coefficients. The analysis is made on evaluating BER, NMSE & Complexity of the three prediction algorithms namely all correlation prediction, FSS predictor and reduced complexity predictor.

Index Terms: Channel Prediction, FSS, OFDM, MIMO.

1. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) is widely used in high data rate communication systems since it is robust against time dispersion in multipath fading channels and can be easily implemented. By dividing the total bandwidth into several parallel sub channels, OFDM also has the ability to adaptively allocate different bit rates and transmission powers to different sub channels and support the possibility of dynamic spectrum use. Hence, OFDM has been suggested as one of the best candidates for modulation in cognitive radio.

The OFDM signal generated by the system in Figure 1 is at baseband; in order to generate a radio frequency (RF) signal at the desired transmit frequency filtering and mixing is required. OFDM allows for a high spectral efficiency as the carrier power and modulation scheme can be individually controlled for each carrier. The data is given to the modulation block. That inverse Fourier transform is applied for that data signal. The output signal is transmitted through the digital to analog converter. The output of the base band OFDM signal is passed to analog to digital converter. Again Fourier transform is applied for that. The demodulated signal is taken from the output .However in broadcast systems these are fixed due to the one-way communication. The basic principle of OFDM is to split a high-rate data stream into a number of lower rate streams that are transmitted simultaneously over a number of subcarriers.

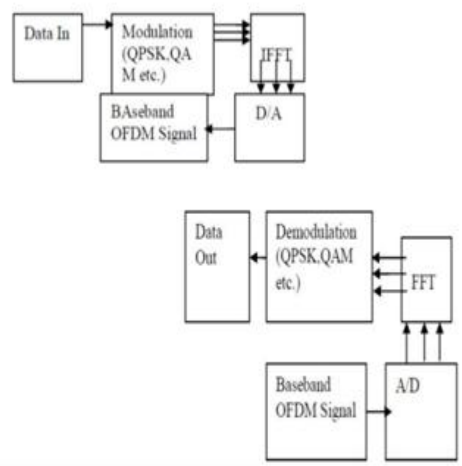

Figure 1: Network diagram of OFDM Transmitter and Receiver

2. OFDM System Model

Consider a MIMO-OFDM system with M transmit antennas, N receive antennas, and K subcarriers. At the transmitter, the transmitted symbol X_m(i, k) is transformed into the time domain signal at the m-th transmit antenna, i-th symbol time and the k-th subcarrier using IFFT. Then, a cyclic prefix (CP) is inserted to avoid inter-symbol interference. At the receiver, the CP is removed before the FFT process. We assume that the CP is greater than the maximum delay spread of channel, and the time and frequency synchronization is perfect, such that the received symbol at the n-th receive antenna can be represented as

$$y_n(i,k) = \sum_{m=1}^{M} H_{n,m}(i,k)\, X_m(i,k) + Z_n(i,k)$$

where $H_{n,m}$(i, k) is the frequency response of the channel impulse response (CIR) at the k-th subcarrier and the i-th symbol time for the (m, n)-th antenna pair. Z_n(i, k) is the background noise plus interference term of the n-th receive antenna, which can be approximated as a zero mean additive white Gaussian noise (AWGN) with variance σ^2Z.

- **Channel Model**

The impulse response of the wireless channel can be represented as

$$h_{n,m}(t,T) = \sum_{l=0}^{L_{n,m}-1} h_{n,m}(t,l)\,\delta(T - T_{n,m}(l))$$

where $L_{n,m}$ is the number of multiple radio path of the (m, n)- th antenna pair, δ(·) is the Kronecker delta function, $T_{n,m}$(l) and $h_{n,m}$(t, l) are the delay and complex-value CIR at time t of the l-th path from the (m, n)-antenna pair respectively. Let $H_{n,m}$(t, f) be the frequency response of the time domain CIR $h_{n,m}$(t, T).

In other words, the spatial correlation matrix of the MIMO channel is given by

$$R_{MIMO} = R_{MS} \otimes R_{BS}$$

where ⊗ represents the Kronecker product, R_{MS} and R_{BS} are spatial correlation matrices at the mobile station (MS) and the base station (BS) respectively.

- Pilot Pattern and Least-Squares Channel Estimation
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Where pilots and data symbols are sent exclusively in the time-frequency domain as

$$\begin{Bmatrix} d_m(i,k), data \\ p_m(i,k), pilot\ at\ m-th\ transmit\ antenna \\ 0 \quad ,pilot\ at\ other\ transmit\ antenna \end{Bmatrix}$$

We perform ma least square (LS) channel estimation at the pilot locations using the received symbol y_n i, k) and the known pilot symbol x_m(i, k), given as

$$\hat{H}_{n,m}(i,k_{m,l}) = y_n(i,k_{m,l}) / x_n(i,k_{m,l})$$

where $\hat{H}_{n,m}(i,k_{m,l})$ is the ideal channel coefficient and $Z'_{n,m}$(i, $K_{m,l}$)is the estimation error denoted as a zero mean AWGN with variance $\sigma_z'^2$.

- **Spatial-temporal channel prediction**

Firstly, the time-domain channel coefficient of every channel pair (m, n) can be estimated by conventional methods, e.g. IFFT with interpolation, reduced LS and LMMSE

$$\hat{h}_{n,m}(i,l) = \frac{1}{k}\sum_{k=0}^{k-1} \hat{H}_{n,m}(i,K)\, e^{j2\pi lk/k}$$

Here, we suppose the channel delay $T_{n,m}$(l) of every tap is an integer multiple of sampling interval. Then, all of the energy from the path will be mapped to the zero to L -1 taps.

Subsequently, a MIMO predictor is performed to predict the time domain channel impulse response $h_{n,m}$ (i+p, l) for each delay l = 0. . . L − 1, where L − 1 represents the channel's maximum delay, and p denotes the prediction length. Due to the WSSUS property, as mentioned earlier, $h_{n,m}$(i + i, l) and $h_{n',m'}$(i, l')are uncorrelated for l ≠ l_. Therefore, the MIMO predictor for the l-th tap only needs to consider the corresponding tap of every channel pair (m, n).. Finally, the frequency domain channel coefficient ˆ$\hat{H}^{pre}_{n,m}$(i+ p, k) is obtained from the predicted time-domain impulse response sample $\hat{h}^{pre}_{n,m}$(i+ p, k) via K-points FFT.

- **Prediction algorithm**

We begin with the AR model, which can capture most of the fading dynamics. In fact, a thorough comparison of different channel prediction algorithms is performed. Their conclusion is that the AR approach outperforms other prediction modeling for measured channels. Define p as the prediction length. For every tap of the channel, Q current and previous estimated coefficients of the channel are considered. Denote $\hat{h}^{pre}_{n,m}$(i+ p, k) the data set $\hat{h}$ is utilized

2.1Extreme predictors

We first introduce two extreme prediction methods, which will be helpful to introduce our algorithms.

- SISO predictor: A traditional prediction algorithm is called the SISO predictor, which ignores the spatial correlation and only considers the temporal correlation. To predict $\hat{h}^{pre}_{n,m}$(i+ p, l) the data set $\hat{h}_{n,m}$(i,l) is used with a Q-order MMSE filter ws as

$\hat{h}^{pre}_{n,m}$ (i+ p, l) = $w_S^H\ \hat{h}_{n,m}$ (I,l)

$$\mathbf{w}_s = \arg\min \mathrm{E}\left\{\left|\left|h_{n,m}{}^{?}(i+p,l) - \mathbf{w}_s^H\ \hat{\mathbf{h}}_{n,m}\ (\mathrm{i},\mathrm{l})\right|\right|^{2}\right\}$$

The MSE is given by

$$\epsilon_s = \mathrm{r_t}(0) - \mathrm{r}_s^T(\mathrm{R}_S + \beta^2 \mathrm{I})^{-1}\mathrm{r}_s$$

- All-correlation predictor: Then, we introduce the prediction algorithm at the other extreme: all-correlation predictor, which exploits all the possible spatial-temporal correlations [18]. This method is also a general case of JST filtering method [28]. The JST filtering in [28] assumes that different transmit antennas are uncorrelated and only considers the spatial correlation of receive antennas, while the all-correlation predictor considers both the temporal and spatial correlations. The data set h is used to predict $\hat{h}^{pre}$ (i+ p, l) where a M × N × Q-order MMSE filter $\mathbf{w}_{2D}$ is applied as

$$\hat{h}^{pre}_{n,m}(\text{i+ p, l}) = w_{2D}^H\ \hat{h}$$

The MSE Is

$$\epsilon_{2D} = \mathrm{r_t}\ 0\ -\ \mathrm{r_s} \times \mathrm{R_{MIMO}}^{(\mathrm{N-\ m-1\ +n}}\ {}^{\mathrm{T}}\ \mathrm{R_s} \times \mathrm{R_{MIMO}} + \beta^2 \mathrm{I}\ ^{-1}\ \mathrm{r_s} \times \mathrm{R_{MIMO}}^{(\mathrm{N-\ m-1\ +n})}$$

2.2 Forward-stepwise subset (FSS) predictor

A reduced order AR predictor is proposed in this subsection, which aims to reduce the computational burden of the all correlation predictor. In this algorithm, the observations are not considered to be equally important for prediction. Some observations just offer little information for the AR model. Particularly, if a datum is independent with the predicted datum, then the datum has no help for prediction. Therefore, we come up with the idea that the most helpful data can be chosen to create the AR prediction model.

The key problem remained is how to measure the helpfulness of each datum. Suppose we have already chosen Q_ data from ˆh, where Q_ is a tradeoff between the prediction precision and complexity, to form a Q_ × 1 vector ˜h. The prediction AR model is

$$\hat{h}^{pre}_{n,m}(\text{i+ p, l}) = w_B^H\ \hat{h}$$

$$\epsilon_{B = \mathrm{r_t}}\ (0)$$

2.3 Reduced-complexity FSS predictor

In this subsection, a prediction algorithm is introduced which aims to further reduce the computational complexity of FSS method. The key idea is to select the data incrementally for prediction from the correlation's view. If the new observation has a high correlation with the selected data in previous steps, then the new observation cannot provide more new information and may help little. Therefore, the considering value $\hat{h}_k$ in the k-th step can be chosen by the analysis of the selected data $\hat{h}_1$ . . . ˜$\tilde{h}_{k-1}$]. Based on this idea, the k-th element is chosen as follows.

- First-step: according to MMSE criterion and AR model

$\hat{h}^{pre}_{n,m}$(i+ p, l) = $w_R^H\ \hat{h}$ we get W_R where $\hat{h} = [\ \tilde{h}_1, \underbrace{\ldots\ldots\ldots}, \tilde{h}_{k-1}\ ]^T$

- Second-step: Residual = $h_{n,m}(i+p,l) - w_R^H\ \hat{h}$
  the $\tilde{h}_k$ is the selected data which is most correlated with the residual.

3. SIMULATION RESULTS

A MIMO – OFDM system is considered for simulation. The performance of the proposed predictor is compared with all correlation predictor and reduced complexity forward stepwise subset predictor. The BER, NMSE performance and computational complexity analysis are shown in fig 2, 3 & 4 respectively. Simulation results show that the prediction performance can be effectively improved by exploiting the spatial correlation, especially when the spatial correlation is relatively high.

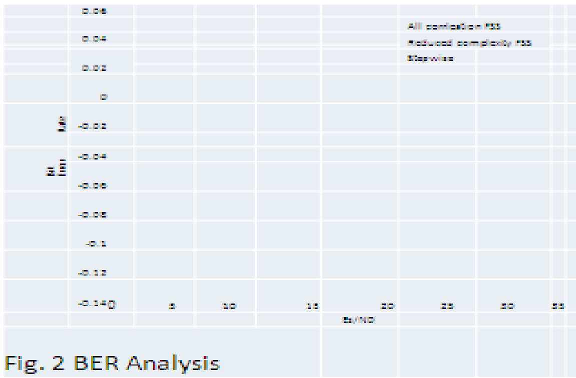

Figure 2: BER Analysis

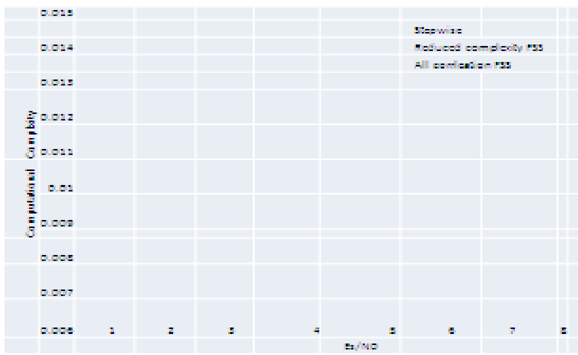

Figure 3: Computational complexity analysis

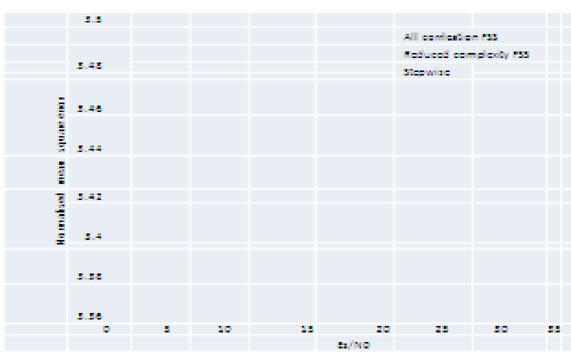

Figure 4: NMSE Analysis

4. CONCLUSION

The existing system derives a novel channel prediction framework for MIMO-OFDM systems which takes both spatial and temporal correlations into account. Second, the system proposes two MIMO prediction algorithms which select the useful data for AR modeling. The FSS predictor employs the optimal data selection strategy, which requires huge computations. Among three prediction algorithms FSS predictor shows the better results than the other algorithms.

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