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DRM Channel Estimation via OMP Algorithm

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Abstract: Digital Radio Mondiale (DRM) standard is the most mature digital broadcasting system standard all over the world. Due to the limited spectrum characteristics of DRM communication systems, pilot-based DRM channel estimation brings great challenges. In this paper, the channel estimation problem is transformed into a sparse recovery problem by leveraging the compressed sensing problem. Subsequently, the orthogonal matching pursuit (OMP) sparse recovery algorithm is employed to obtain accurate estimation performance with a lower pilot overhead. Compared with the traditional least square algorithm, simulation results demonstrate that the OMP-based channel estimation algorithm can obtain accurate estimation results with lower pilots, and improve the spectrum utilization while improving the estimation performance.

Keywords: Channel Estimation, OMP Algorithm, Pilot Design, Compressed Sensing.

1. Introduction

The traditional analog AM radio receiver with wide coverage, low cost, suitable for fixed and mobile reception and other advantages, has been around the world as the best means of coverage of regional and international broadcasting, but also has the sound quality difference, the single business volume defect susceptible to interference etc [1-3]. With the advent of modern digital broadcasting technology, such as digital satellite broadcasting, digital audio broadcasting and so on, it is particularly urgent to digitize analog amplitude modulation broadcasting. Digital Radio Mondiale (DRM) standard is the most mature digital broadcasting system standard all over the world. It puts forward a solution to the digitalization of the medium and short wave amplitude modulation broadcasting under 30MHz, and extends the single audio information to various carriers such as data, text, graphics and video in function, so as to create an excellent platform for the diversified services of digital broadcasting.

Because of HF channel is spectrum constrained time-varying multipath channel, in order to make full use of spectrum resources, OFDM technology is used in DRM standard to overcome the signal interference and fading caused by time-varying multipath characteristics of channels For the OFDM system, the channel sate information is required for coherent demodulation and channel equalization at the receiver, and channel estimation technology plays a very important role in it. With the development of the research, many wireless channels have strong sparse characteristics in the time domain, that is, there are only a few significant multipath components in the channel impulse response, and almost all the other amplitudes of the impulse response are zero.

In the field of channel estimation, related research has found that the common wireless multipath channel is sparse channel, and the theory of Compressed Sensing (CS) has been applied to channel estimation, and proposed Compressive Channel Sensing (CCS) [4, 5]. CS theory reveals that if the signal is compressed, then the high dimensional signal can be transformed into low dimensional signal through the perception matrix, and then the original signal can be reconstructed from a small number of low dimensional signals with high probability by solving the optimization problem. The core problem of compressed sensing is sparse signal compression measurement and recovery, and the channel estimation process is precisely the measurement and recovery of sparse channel impulse response. Therefore, the CS theory is applied to sparse channel estimation, which can take full advantage of the inherent sparse nature of the channel. It can obtain accurate and reliable estimation results with fewer pilots, and improve the channel estimation performance while improving spectrum utilization.

The paper is organized as below. In Section 2, the theory of compressed sensing is recalled. Section 3 shows channel estimation problem is modeled as CS sparse signal reconstruction problem, and channel model is established. In Section 4, experiments are carried out in order to simulate the performance of the proposed channel estimation model. Finally, the conclusion is given in Section 5.

2. Compressed Sensing

During the course of the last decade, a new sampling theory has emerged, known as compressive sampling or compressed sensing, which was introduced about 10 years ago as an effective and efficient way of sensing and acquiring data. While Shannon sampling theory only utilizes the bandwidth information of the signal, compressed sensing relies on the crucial observation that data we are interested in acquiring typically are structured. To be concrete, they often possess a sparse or nearly sparse representation in a certain basis or dictionary.

The CS sampling is a quite new framework that enables to get exact and approximate reconstruction of sparse or almost sparse signals from incomplete measurements. CS theory considers a k-sparse signal $x \in \Re^N$ with k nonzero elements, then the system can get the measurements $x \in \Re^M$ from linear projection in the noiseless setting.

$$y = Hx \tag{1}$$

Where $H \in \Re^{M \times N}$ is the sensing matrix with .CS can recover the signal x from the measurement vector y. The solution to this system by solving the following l0 -minimization problem.

$$\min \|x\|_0 \quad s.t. \quad Hx = y \tag{2}$$

However, it is well-known that (2) is NP-hard problem in general, which is a non-convex optimization problem. There are two kinds of solution to recover the k-sparse signal x. The method is greedy algorithms for l0 -inimization, such as orthogonal matching pursuit (OMP), which can exactly recover x. The second method is to found convex relationship to (2), and x can recover via l1 -minimization

$$\min \|x\|_1 \quad s.t. \quad Hx = y \tag{3}$$

This solution to recover the k-sparse signal x can be completed by the basis pursuit algorithm.

3. Channel Model

The channels to be considered are the LF, MF and HF broadcast radio transmission channels. In principle all three are multipath channels because the surface of the earth and the ionosphere are involved in the mechanism of electromagnetic wave propagation [7, 8]. The approach is to use stochastic time-varying models with a stationary statistics and define models for good, moderate and bad conditions by taking appropriate parameter values of the general model. One of those models with adaptable parameters is the Wide Sense Stationary Uncorrelated Scattering model (WSSUS model).

$$h(t) = \sum_{l=0}^{L-1} \rho_l c_l(t) \delta(t - \Delta_l) \tag{4}$$

This is a tapped delay-line ,where ρ_l is the attenuation of the path number L, Δ_l is the relative delay of the path number L, and the time-variant tap weights $c_l(t)$ are zero mean complex-valued stationary Gaussian random processes. The magnitudes are Rayleigh-distributed and the phases are uniformly distributed.

We suppose that OFDM uses N subcarriers in the DRM system, where P pilot subcarriers are used. The equivalent discrete channel impulse response is $h = [h(0), h(1), \cdots, h(L-1)]^T$, L is the channel length, and the received signal Y is represented:

$$Y = XH + W = XFh + W \tag{5}$$

Where $X = diag(X_1, X_2, \cdots X_N)$ is $N \times N$ diagonal matrix, H is the channel frequency response, W is the Gauss white noise in the frequency domain, and F is the first L column of the standard Fourier matrix:

$$F = \frac{1}{\sqrt{N}} \begin{bmatrix} f^{00} & \cdots & f^{0(L-1)} \\ \vdots & & \vdots \\ f^{(N-1)0} & \cdots & f^{(N-1)(L-1)} \end{bmatrix}, \qquad f = e^{-\frac{j2\pi}{N}} \tag{6}$$

By the selecting matrix S, the P pilot signals are selected from the N carriers. According to the selection matrix S, the P line corresponding to the pilot position is selected from the diagonal matrix X, and the pilot signal at the receiver is computed

$$Y_{P\times1} = X_{P\times P}F_{P\times L}h_{L\times1} + W_{P\times1} = A_{P\times L}h_{L\times1} + W_{P\times1} \tag{7}$$

In equation (7), $Y_{P\times1}$, $X_{P\times P}$, $F_{P\times L}$ and $W_{P\times1}$ are all known signals for the received end, and they can be used to calculate $h_{L\times1}$. The response value H in frequency domain can be obtained.

$$H_{N\times1} = W_{N\times L}h_{L\times1} \tag{8}$$

The channel impulse response $h_{L\times1}$ has very few nonzero values, so it is a sparse channel. Solving $h_{L\times1}$ is a typical sparse signal reconstruction problem, which can be accomplished by the CS reconstruction algorithm. Compared with the traditional channel estimation method, it can obtain accurate and reliable estimation results with fewer pilots, and improve the channel estimation performance while improving the spectrum utilization.

4. Analysis of Simulation Results

The channel estimation method based on compressed sensing effectively utilizes the sparse nature of the channel, uses fewer pilots to complete channel estimation, and improves the transmission efficiency of the system. In this section, the basic principle of DRM channel estimation based on compressed sensing is verified by simulation experiments, and the reconstruction algorithm uses OMP algorithm. The influence of the insertion mode and number of pilots on the reconstruction performance is analyzed, and the Mean Square Error (MSE) and the bit error rate (BER) are estimated. The system simulation is assumed that the system is ideal synchronous and without channel coding. The robust mode adopts B mode and chooses typical shortwave channel (channel 3), and the specific simulation parameters are shown in the Table 1.

Table 1. System Parameters

Parameter	Value
Sampling interval T (us)	83.33
OFDM symbol time T_s (ms)	26.67
Number of subcarriers N	256
Subcarrier interval Δf (Hz)	46.875
Guard interval N_g	64
Baseband modulation mode	QPSK
Multipath number of channel K	4
Channel length L	50
SNR (dB)	0-30
Number of iterations of simulation M	1000

4.1. The Influence of Pilot Pattern on Channel Reconstruction by OMP Algorithm

When the OMP algorithm is used to complete the channel estimation, three pilot pattern placement

methods are selected: continuous, uniform and random. As shown in Figure 1, continuous refers to the P pilot continuously placed throughout the N subcarrier, uniform refers to the P pilot interval between the same numbers, which are uniformly distributed throughout the N subcarrier, and random refers to the P pilot randomly distributed in the N subcarrier.

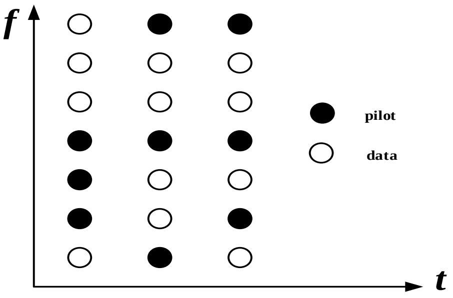

Figure 1. The arrangement of three pilot patterns

From the simulation results of Figure 2 and Figure 3, it can be seen that the channel estimation performance of the OMP algorithm with the continuous permutation mode is the worst, and the pilot pattern of the uniform arrangement is second, and the random pattern of the pilot pattern has the best performance. The reason is that the location of pilot placement determines the form of the perception matrix A directly, and the randomly arranged pilot pattern is closer to the RIP property, which makes the estimation of channel sparse position more accurate and improves the performance of signal reconstruction.

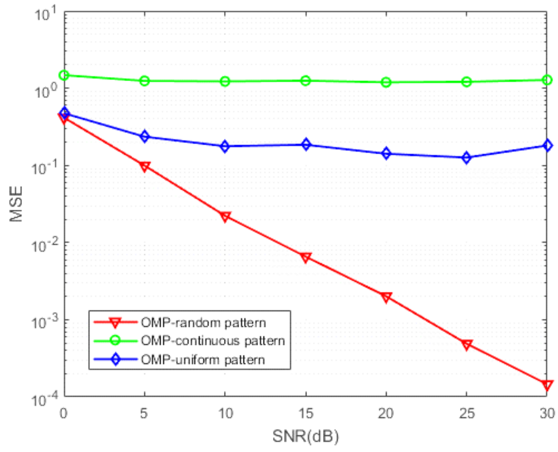

Figure 2. P=26, MSE versus SNR

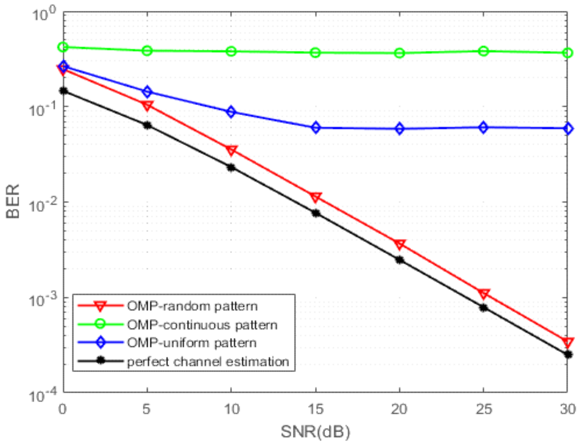

Figure 3. P=26, BER versus SNR

4.2. The Comparison of Channel Estimation Performance Between OMP and LS

Through the previous simulation, we find that OMP algorithm achieves the best channel estimation performance when the pilots are randomly selected, and MSE is very large if the pilots are equally spaced or continuously selected. In order to reasonably compare the channel estimation performance of the two algorithms, the pilot position of the OMP algorithm is randomly selected, and the pilot position of the LS algorithm is uniformly selected. It can be seen from the MSE of Figure 4 that the MSE of the LS algorithm using the frequencies of 26 and 43 is higher than that of the OMP algorithm. When SNR is less than 5 dB, the superiority of OMP algorithm is not obvious, but with the increasing of signal to noise ratio, the superiority of OMP algorithm is becoming more and more obvious. When SNR is 30dB, the MSE of OMP algorithm is smaller than that of LS algorithm 8 dB. From the BER of Figure 5, it can be seen that the channel estimation performance of the LS algorithm of the pilot P=43 is only 26 pilots if it is replaced by the OMP algorithm. The system not only reduces the percentage of frequency to total carrier number from 16.8% to 10.1%, but also estimates the performance of OMP algorithm better than that of LS algorithm. At the same time, the saved pilot can transmit data signals, thus improving the throughput of the whole system.

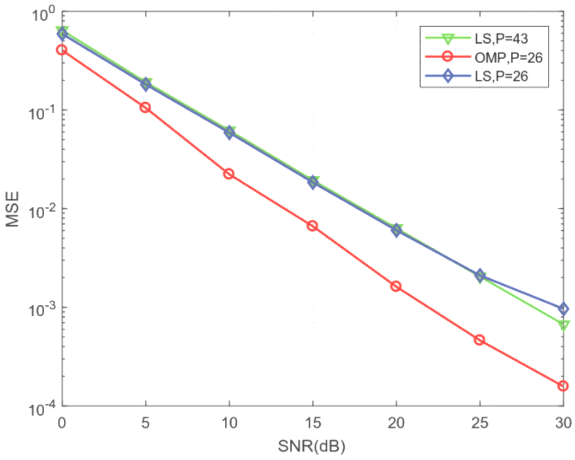

Figure 4. MSE versus SNR for OMP and LS

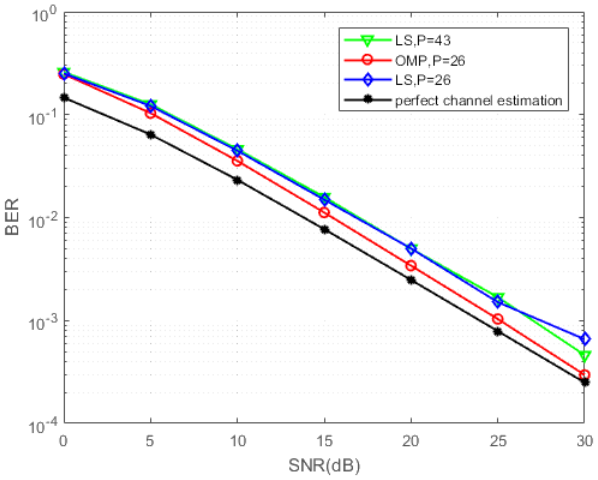

Figure 5. BER versus SNR for OMP and LS

4.3. The Influence of Pilot Number on Channel Reconstruction by OMP Algorithm

In the channel estimation based on compressed sensing, the number of pilots corresponds to the number of measurements in the OMP algorithm. The main purpose of this experiment is to study the influence of pilot number on the performance of OMP channel reconstruction algorithm. In this experiment, the pilot arrangement is randomly placed, and Figure 6 shows the MSE corresponding to the different number of pilots by the OMP algorithm. It can be seen from the simulation results that with the increase of the number of pilots, the performance of channel estimation based on OMP reconstruction algorithm is getting better and better, but when the pilot frequency is greater than 26, the effect of channel estimation is getting smaller and smaller. Figure 7 is the BER comparison of the system with different pilot numbers. From the graph, it can be seen that the BER almost overlaps at P=26, P=32 and P=43, and the channel estimation performance is close to the ideal channel estimation at this time. Considering the effectiveness and reliability of the system transmission, it is not significant to continue to increase the number of pilots, but it will reduce the spectrum efficiency of the system. At the same time, the simulation results verify the relationship between measurement value and sparsity in compressed sensing theory. When the number of measurements is 4-6 times of sparse vector sparsity, the reconstruction probability of the signal becomes high enough.

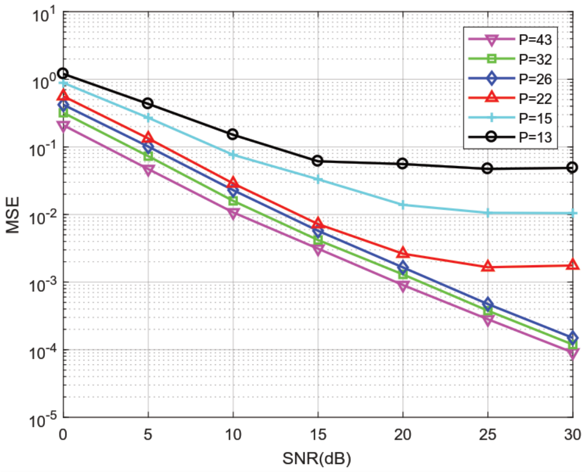

Figure 6. MSE versus SNR based on OMP algorithm

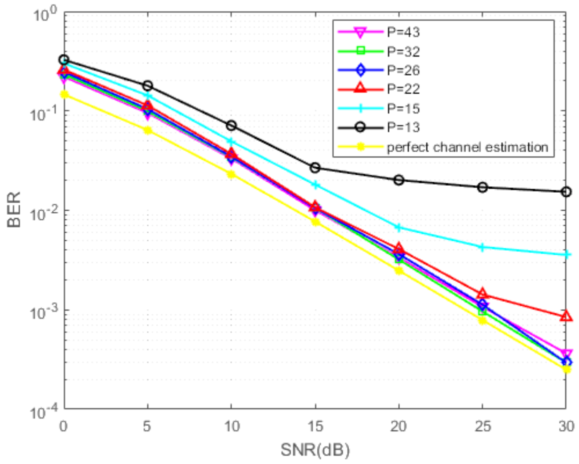

Figure 7. BER versus SNR based on OMP algorithm

5. Conclusion

In this paper we formulate HF channel estimation of DRM standard as a sparse recovery problem. It is shown that the CS algorithms are much better than the traditional LS method. The channel estimation algorithm based on CS cannot only obtain accurate and reliable estimation results with fewer pilots, but also improve spectrum utilization while improving the channel estimation performance. Therefore, the CS-based method of pilot allocation is a very efficient and practical method to improve the performance of channel estimation in HF communication systems.

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