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Research Paper

Compressive Sensing Based OFDM Channel Estimation -a Survey

Engineering

KEYWORDS : Channel estimation, OFDM, Compressive Sensing (CS), LS estimation

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ABSTRACT

for wireless multimedia applications, system with higher data rate is required. Furthermore, the frequency spectrum has become a limited and valuable resource, making it necessary to utilize the available spectrum efficiently and coexist with other wireless systems. OFDM modulation is widely used in communication systems to meet the demand for ever increasing data rates. Channel estimation is one of the key challenges in OFDM. It is not possible to make reliable data decisions unless a good channel estimate is available. Many methods have been proposed for efficient channel estimation in OFDM systems. The purpose of this article is to present a survey of the published literature in dealing with compressive sensing based channel estimation of OFDM systems

INTRODUCTION

OFDM is becoming widely applied in wireless communications systems due to its high rate transmission capability with high bandwidth efficiency and its robustness with regard to multipath fading and delay [1]. OFDM divides the available spectrum into a number of overlapping but orthogonal narrowband sub channels, and hence converts a frequency selective channel into a non frequency selective channel. Moreover, ISI is avoided by the use of CP, which is achieved by extending an OFDM symbol with some portion of its head or tail. With these vital advantages, OFDM has been adopted by many wireless standards (DAB, DVB, and DSL) standards and wireless LAN standards and as the core technique for the fourth-generation (4G) wireless mobile communications. A baseband OFDM system is shown in Figure1.

In the middle 1960s, OFDM scheme was introduced by Chang [2] for parallel transmission over a band limited channel without intercarrier interference (ICI) and ISI. He proposed dividing a frequency-selective fading channel into a number of flat fading channels, which simplifies the receiver design. The sub channels are orthogonal to each other, which results in higher spectral efficiency. The transmitter and receiver of an OFDM system must be carefully designed so that orthogonality can be maintained between the sub channels.

As the number of subcarriers increases, implementation of an OFDM system becomes more complex considering the requirements of modulation, synchronization and coherent demodulation. In particular, it was impractical to implement

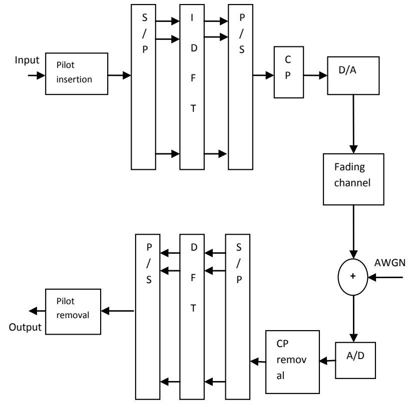

Figure 1: Baseband OFDM System

the modulation using oscillators at the required frequencies. In the 1970s, the Discrete Fourier Transform (DFT) was proposed by Weinstein and Ebert [3] for modulation and demodulation in OFDM systems. This is referred to as DFT-based OFDM, and significantly reduces the implementation complexity of OFDM systems. In a DFT-based OFDM system, the DFT is used to transform the data from the frequency domain to the time domain and provide the orthogonality between subcarriers. A guard interval is employed to reduce the effects of multipath channels. Even though the proposed system does not achieve perfect orthogonality among the subcarriers over a time dispersive channel, it has made modern low-cost OFDM systems possible today.

Another important contribution to OFDM was the cyclic prefix (CP), which was proposed by Peled and Ruiz in 1980 to solve the orthogonality problem [4]. A cyclic prefix, instead of the conventional null band, is added at the beginning of the OFDM symbol after inverse fast Fourier transform (IFFT) procedure. If the length of the cyclic prefix is equal to or longer than the channel length, the linear circular channel is converted into a cyclic circular channel, which ensures orthogonality over a time dispersive channel and eliminates the ISI between subcarriers. The cost is a loss in the effective data rate. With the improvement in implementation technology and increased demand for efficient bandwidth usage, OFDM became a popular wireless technology in the 1990s.

In wireless systems, transmitted information reaches to receivers after passing through a radio channel. For conventional coherent receivers, the effect of the channel on the transmitted signal must be estimated to recover the transmitted information. As long as the receiver accurately estimates how the channel modifies the transmitted signal, it can recover the transmitted information. Channel estimation can be avoided by using differential modulation techniques, however, such systems result in low data rate and there is a penalty for 3–4 dB SNR.

LITERATURE SURVEY

In OFDM based systems, the data is modulated onto the orthogonal frequency carriers. For coherent detection of the transmitted data, these sub-channel frequency responses must be estimated and removed from the frequency samples. Like in single carrier systems, the time domain channel can be modelled as a FIR filter, where the delays and coefficients can be estimated from time domain received samples, which are then transformed to frequency domain for obtaining the CFR. Alternatively, radio channel can also be estimated in frequency domain using the known (or detected) data on frequency domain sub-channels. Instead of estimating FIR coefficients, one tap CFR can be estimated.

Channel estimation techniques for OFDM based systems can be grouped into two main categories: blind and non-blind. The blind channel estimation methods exploit the statistical behaviour of the received signals and require a large amount of data . Hence, they suffer severe performance degradation in fast fading channels. On the other hand, in the non blind channel estimation methods, information of previous channel estimates or some portion of the transmitted signal are available to the receiver to be used for the channel estimation.

The non-blind channel estimation can be studied under two main groups: data aided and DDCE. In data aided channel estimation, a complete OFDM symbol or a portion of a symbol, which is known by the receiver, is transmitted so that the receiver can easily estimate the radio channel by demodulating the received samples.

In the DDCE methods, to decode the current OFDM symbol the channel estimates for a previous OFDM symbol are used. The channel corresponding to the current symbol is then estimated by using the newly estimated symbol information. Since an outdated channel is used in the decoding process, these estimates are less reliable as the channel can vary drastically from symbol to symbol.

There are basically three basic blocks affecting the performance of the non-blind channel estimation techniques. These are the pilot patterns, the estimation method, and the signal detection part.

There are several basic techniques to estimate the radio channel in OFDM systems. The estimation techniques can be performed using time or frequency domain samples. These estimators differ in terms of their complexity, performance, practicality in applications to a given standard, and the a priori information they use. The a priori information can be subcarriers correlation in frequency, time, and spatial domains. Moreover, the transmitted signals being constant modulus, CIR length and using a known alphabet for the modulation can also be a priori information. The more the a priori information is exploited. For frequency domain channel estimates, MSE is usually considered as the performance measure of channel estimates. BER performance is mainly used when the performance of OFDM system with the channel estimation error is to be evaluated.

2.1. NON BLIND TECHNIQUES

In data aided channel estimation, known information to the receiver is inserted in OFDM symbols so that the current channel can be estimated. Two techniques are commonly used: sending known information over one or more OFDM symbols with no data being sent, or sending known information together with the data. The previous arrangement is usually called channel estimation with training symbols while the latter is called pilots aided channel estimation.

Channel estimation employing training symbols periodically sends training symbols so that the channel estimates are updated. In some cases training symbols can be sent once, and the channel estimation can then be followed by decision directed type channel estimation.

In the training mode, all the subcarriers of an OFDM symbol are dedicated to the known pilots. Once the channel is estimated over the training OFDM symbols, it can be exploited for the estimation of the channels of the OFDM symbols sent in between the training symbols. Depending on the variation of the channel along time, different techniques can be utilized. A very common method is to assume the channel being unchanged between OFDM training symbols . In this method, the channel that is estimated at training symbols is used for the subsequent symbols until a new training sequence is received. The channel is then updated by using the new training sequence, and the process continues. However, these approaches introduce an error floor for non-constant channels. The highest performance degradation occurs at the symbols farthest from the training symbols. For the fast varying channels, interpolation methods can be utilized in time domain.

In the pilot mode, only few subcarriers are used for the initial estimation process. Depending on the stage where the estimation is performed, estimation techniques will be considered under time and frequency domains techniques. In frequency domain estimation techniques, as a first step, CFR for the known pilot subcarriers is estimated. These LS estimates are then interpolated/extrapolated to get the channel at the non-pilot subcarriers..

A popular class of coherent demodulation for a wide class of digital modulation schemes has been proposed by [5] and is known as Pilot Symbol Assisted Modulation. The main idea of PSAM channel estimation is to multiplex known data streams with unknown data. Conventionally the receiver firstly obtains tentative channel estimates at the positions of the pilot symbols by means of remodulation and than compute final channel estimates by means of interpolation. The main disadvantage of this scheme is the slight increase of the bandwidth.

In [6], superimposed pilot sequences are introduced for the purpose of channel estimation, and main idea here is to linearly add a known pilot sequence to the transmitted data sequence and perform joint channel estimation and detection in the receiver.

Piecewise Linear Interpolation — Two of the simplest ways of interpolation are the use of piecewise constant and linear interpolation. In the piecewise constant interpolation, the CFR between pilot subcarriers is assumed to be constant, while in piecewise linear interpolation the channel for non-pilot subcarriers is estimated from a straight line between two adjacent pilot subcarriers.

In the first method, acceptable results can be obtained if the CFR is less frequency selective or the CIR maximum excess delay is very small. Such a constraint makes the CFR at the subcarriers very correlated that CFR at a group of subcarriers can be assumed to be the same. In piecewise linear interpolation some variation is allowed between the pilot subcarriers. Such an approach can result in a lower MSE since noise averaging is performed. Moreover, when the channel becomes more frequency selective, the piecewise linear interpolation results in a better performance compared to the piecewise constant.

Starting from the methods using the least a priori information, in this article we will review channel estimation methods such as LS estimation, ML, transform domain techniques, LMMSE and compressive sensing.

2.1.1. LS ESTIMATION

Before going into the details of the estimation techniques, it is necessary to give the LS estimation technique as it is needed by many estimation techniques as an initial estimation. Starting from system model of SISO-OFDM.

$$Y[n,k]=X[n,k]H[n,k]+W[n,k] \tag{1}$$

LS estimation of in matrix notations is given by,

$$H_{LS} = \mathrm{diag}(X)^{-1}\, Y + \mathrm{diag}\,(X)^{-1}\, W \tag{2}$$

The MSE of the LS estimation is given by,

$$MSE_{LS} = K/[E_H\ .SNR] \tag{3}$$

Where = $E_H = E\ \{ H[n,k] \}$

LS method, in general, is utilized to get initial channel estimates at the pilot subcarriers, which are then further improved via different methods. It is also common to introduce CIR to Equation (1). To exploit CIR length for a better performance, Equation (1) can be modified as

$$Y=\mathrm{diag}(X)Fh+W \tag{4}$$

Where H=Fh

The LS estimation

$$\hat{H}=Q_{LS}\, F^H\, \mathrm{diag}(X)^H\, Y \tag{5}$$

Where (6)

Q_{LS}=(F^H diag(X)^H diag(X)F-^{1}

The above LS estimation will be referred as time domain LS. When no assumptions on the number of the CIR taps or length are made, then the time domain LS reduces to that of frequency domain, and it does not offer any advantages. However, with the assumption that there are only L number of channel taps, which then reduces the dimension of the matrices F and hence Q, an improved performance due to the noise reduction can be obtained. The resultant LS estimation has higher computational complexity than the frequency domain LS but the performance increase is the plus side of the approach. The increase in the performance can be considered as the exploitation of subcarrier correlation.

It can be observed that when the number of pilots is greater than the channel length and the noise is AWGN, the time domain LS estimate is equivalent to the ML estimate .The ML estimate makes the assumption about the CIR length, which improves the performance of the estimation accuracy. LMMSE is widely used in the OFDM channel estimation since it is optimum in minimizing the MSE of the channel estimates in the presence of AWGN. LMMSE uses additional information like the operating SNR and the other channel statistics. LMMSE is a smoother / interpolator / extrapolator, and hence is very attractive for the channel estimation of OFDM based systems with pilot subcarriers. However, the computational complexity of LMMSE is very high due to extra information incorporated in the estimation technique.

2.1.2. TRANSFORM DOMAIN TECHNIQUE

It was mentioned that in general the CIR length is much smaller than the number of pilot subcarriers, that is, L < Np. When an orthogonal transformation is applied to the CFR at the pilot subcarriers, the transform domain contains L number of significant values, that is, values relatively having more energy or magnitude than the noise. Since the noise is assumed to be AWGN in frequency domain, it is AWGN in transform domain as well. If the significant values of the transform domain signal are retained, and the non-significant ones are treated as zero, then the noise term will be eliminated significantly especially when L << Np. For this operation, some sort of threshold is needed to differentiate between the significant values of the signal and noise terms. The CFR can then be obtained by applying the inverse of the orthogonal transformation, since such an operation will also achieve interpolation for non-pilot subcarriers [7].

Once the CFR is obtained via a transform domain technique, the channel at subsequent OFDM symbols (over time) can be obtained via different methods. The filtering process of transform domain is usually followed by linear interpolation in time domain. Wiener filtering is also found to be effective in noise reduction in time domain. The transform domain techniques exploit the information about the number of significant values in the transform domain and their location. Moreover, more number of pilot subcarriers is used for the interpolation process. Hence, they perform better than the simple interpolation techniques in general. Different transform domain techniques are studied for the channel estimation of OFDM based systems. Fourier, Hadamard, Discrete Cosine, and 2-D Fourier Transformation are few to name.

The performance of the transform domain techniques are heavily dependent on the CIR tap locations, an inaccurate assumption or calculation of CIR tap locations can degrade any of the transform domain techniques drastically. Hence, a transform domain method which inherently uses the information of the channel taps is expected to provide better results.

2.1.3.LMMSE ESTIMATION

LMMSE is extensively used in the OFDM channel estimation since it is optimum in minimizing the MSE of the channel estimates in the presence of AWGN. LMMSE uses additional information like the operating SNR and the other channel statistics. LMMSE is a smoother/interpolator /extrapolator, and hence is very attractive for the channel estimation of OFDM based systems with pilot subcarriers. However, the computational complexity of LMMSE is very high due to extra information incorporated in the estimation technique.

For a given linear system model in the form of

$$y=Ax+w \tag{7}$$

LMMSE of the variable is given by,

$$\hat{x} = R_{yx}R_{yy}^{-1}y \tag{8}$$

Where is the cross-covariance between variables and . When the expression in Eq. (8) is applied to the OFDM channel estimation.

$$\hat{H}_{LMMSE} = R_{HH_p} \cdot R_{H_pH_p} + \sigma_w^2(diag(X)diag(X)^H)^{-1}\hat{H}_{LS} \tag{9}$$

can be obtained. Here, is the CFR at the pilot subcarriers, represents the cross-correlation between all the subcarriers and the pilot subcarriers, and represents the auto-correlation between the pilot subcarriers. As can be seen in Eq. 9, LMMSE uses additional information in its estimation process such as the correlation between subcarriers and SNR.

The LMMSE estimation of in Eq. 9 is computationally very heavy. For example, the dependency on the transmitted symbols due to the matrix inversion required at each estimate needs many operations. Moreover, large sized, full matrix multiplication required for a single estimate increases the computational complexity of LMMSE as well. The non-trivial matrix inversion required in the LMMSE estimation is another factor increasing the computational complexity of LMMSE. Therefore, although LMMSE is optimal, without reducing its computational complexity, it is hard to realize its application in practical systems.

The complexity of LMMSE can be significantly reduced if the LMMSE expression is made independent of the transmitted symbols. Although the expression inside the inversion operation also contains the term , which is the auto covariance of the CFR at the pilot tones, does not change for a large number of OFDM symbols since it is a function of channel PDP. Therefore, for a given large number of OFDM symbols, the term can be assumed to be constant, leaving (diag(X)diag(X)^H)$^{-1}$ as the constantly changing parameter from symbol to symbol.

For the computational complexity and noise subspace reduction for LMMSE channel estimation subspace methods are investigated. Using subspace methods, the number of multiplications required for the channel estimate of a single subcarrier is reduced by exploiting SVD [25]. Subspace methods applied to the LMMSE channel estimation disclose the degree of independency of the subcarriers' auto and cross-correlation matrices. As the subcarrier correlation is a function of the channel delay spread, it ultimately reveals long-term significant CIR taps or channel PDP.

Without subspace methods, the complexity of the channel estimation using LMMSE can be reduced considerably by assuming a pre-defined channel length [23]. But, for sparse channels this would mean unnecessary computation when the considerable number of channel taps is smaller than the channel length [24]. With the CIR length being much smaller than the number of the subcarriers, SVD of the auto and cross correlation matrices of CFR result in only as many significant singular values as the significant number of CIR taps. As the noise is assumed AWGN in frequency domain, the SVD decomposition results in equivalent singular values for the noise terms. Hence, it can be anticipated that the noise in frequency domain is equally distributed in the subspace domain with equal energy in all dimension of the subspace. If the subspace due to the noise is eliminated, then noise reduction is achieved [24]. Moreover, due to the formulation of LMMSE, less number of multiplications will be required after the SVD operation.

2.1.4. COMPRESSIVE SENSING TECHNIQUE

Given a low-pass signal, the Nyquist sampling theorem states that if you want to be able to reconstruct the signal from its samples, you must sample the signal at a rate that is greater than twice the signal's bandwidth. As with most rules, there are "exceptions" to this rule. As you will see, compressive sensing, a technique currently being developed by researchers the world over, can be considered an "exception" to the Nyquist sampling theorem. Under certain conditions, even when the Nyquist sampling theorem says that a sensor needs to store samples of a signal per second, compressive sensing lets the sensor store M<<N linear combinations of samples per second.

Compressive sensing is a recently introduced principle and methodology for the efficient reconstruction of sparse signals from few samples. It has found broad application in imaging, data compression, radar, and data acquisition. In a nutshell, compressive sensing is a novel paradigm where a signal that is sparse in a known transform domain can be acquired with much fewer samples than usually required by the dimensions of this domain. The only condition is that the sampling process is "incoherent" with the transform that achieves the sparse representation and "sparse" means that most weighting coefficients of the signal representation in the transform domain are zero. While it is obvious that a signal that is sparse in a certain basis can be fully represented by an index specifying the basis vectors corresponding to non-zero weighting coefficients plus the coefficients – determining which coefficients are nonzero would usually involve calculating all coefficients, which requires at least as many samples as there are basis functions. The definition of "incoherence" usually states that distances between sparse signals are approximately conserved as distances between their respective measurements generated by the sampling process. In this sense the reconstruction problem has per definition a unique solution.

CS [8] is a recently developed mathematical framework, which asserts that a sparsely representable signal can be reconstructed using a small number of linear measurements. For example, consider a signal x,

$$x=\varphi s \tag{10}$$

This is k-sparse in this basis defined by the columns of.

According to CS, if non traditional linear measurements

$$y=\emptyset x \tag{11}$$

In the form of randomized projections are taken, the signal x can be exactly reconstructed with a high probability with a lesser number of samples, from the compressive measurements by solving a convex optimization problem subject to:

$$y=\emptyset\varphi s \tag{12}$$

This can be solved efficiently with linear programming. The key result is that the required number of measurements is linked linearly to the sparsity-k of the signal. The Compression is done at Sensing level rather after the sensing. This leads to a greater reduction of sampling, taking only fewer measurements, M, with

$$M=K\log(N) \tag{13}$$

Where, is the sparsity order in frequency domain, is the original number of samples used.

Taking into account the background literature, as well as the advantages, obtained by exploiting the sparsity property of channel, we shall propose a Compressive Sensing based channel estimation for OFDM.

Considering the sparse distribution of the scattering objects, the OFDM channel becomes sparse in the time domain. Thus, by exploiting this sparsity, a better estimate could be obtained using the time domain. The resulting estimate is then transformed into the frequency domain by use of the FFT algorithm. In this sense, the problem of channel estimation becomes equivalent to finding the sparse Channel Impulse Response (CIR) () from the equation:

$$H_p=F_p.h+W_p \tag{14}$$

Where is the vector of observed channel coefficients at pilot subcarriers, is the sub-matrix of the DFT matrix obtained by keeping the rows of the FFT matrix that correspond to pilot positions and is the frequency-domain noise vector at pilot positions. As stated earlier, in the case of no ISI, the length of the channel cannot exceed the length of the cyclic prefix (NCP). Thus, (11) can be further simplified in the zero ISI case; only the first NCP elements of can have non-zero values.

$$H_p= F_{p\,,CP})\,.h_{CP}+W_p \tag{15}$$

Where $F_{p\,,CP})$ is the sub-matrix of the DFT matrix obtained by keeping only the first NCP columns of F_p.

The area of sparse channel estimation dates back to early nineties. Historically, the problem of sparse-channel estimation using training-based methods was first explored in the literature in the context of underwater acoustic communications. Specifically, prompted by the fact that typical underwater acoustic channels have impulse responses with large delay and Doppler spreads but only a few dominant echoes, an adjustable complexity, recursive least-squares estimation algorithm that ignores the weakest dimensions ("taps") of the channel was proposed in [9] for doubly-selective single-antenna channels using single-carrier waveforms. Afterwards, inspired by the fact that digital television channels and broadband channels in hilly terrains also exhibit sparse structures, Cotter and Rao proposed a sparse-channel estimation method based on the matching pursuit (MP) algorithm for frequency-selective single-antenna channels using single-carrier waveforms [10], Later, the MP-based sparse-channel estimation method of [10] was extended to frequency-selective single- and multiple antenna channels using multi carrier waveforms in [11] and to doubly-selective single-antenna channels using single-carrier waveforms. The channel estimation techniques presented in [10] limited themselves to sparsity in the delay domain, i.e., they did not exploit Doppler sparsity.

In contrast to the MP-based approach, Raghavendra and Giridhar proposed a modified least squares (LS) estimator in [12] for sparse frequency-selective single-antenna channels using multi-carrier waveforms. The idea behind the approach in [12] was to reduce the signal space of the LS estimator by using a generalized Akaike information criterion to estimate the locations of nonzero channel taps.

The CS based PSACE methods are developed for multicarrier systems [13] that can reduce the channel estimation errors and the pilot overhead and hence increase spectral efficiency. In [13] author exploits the delay Doppler sparsity of wireless channels and uses classical basis pursuit algorithm for the recovery. In [13] OFDM channel estimation problem satisfies restricted isometry property (RIP) in case of uniform pilot insertion but they did not consider the virtual sub carriers which cause the RIP condition unsatisfied.

In [14], channel's delay-Doppler sparsity is exploited for doubly-selective fading channels. They exploit a channel's delay-Doppler sparsity to reduce the number of pilot symbols and, hence, increase the spectral efficiency of multi carrier transmissions. However, they do not analyse the RIP of the OFDM channel estimation in the scenario where many virtual subcarriers exist at the both side of an OFDM symbol and the pilots are not uniform inserted for the practical MIMO-OFDM systems.

A main drawback of [12] [13] methods is that they do not consider zero padding in their scenario. In current OFDM standards the bandwidth is not fully occupied; a number of the subcarriers at both edges of the bandwidth are set to zero (hence the name zero padding) to increase the allowable transition band of the analog band pass filter at the receiver. Zero padding results in an unstable frequency to time transformation (ill-conditioned transformation matrix). In addition, due to the lack of pilot in zero padded parts, common time domain techniques are impractical. To overcome this drawback in [15] a sparse channel estimation that works adequately even for zero padded OFDM system called Adaptive Thresholding for Detection of Sparse Signals (ATSSD) is proposed. This method can perform better for both time varying and time invariant channels.

Since OMP and SP have some drawback,[16] propose a hybrid compressive sensing algorithm subspace orthogonal matching pursuit (SOMP). It combines the advantages of both SP and OMP. SOMP first identifies the channel sparsity and then iteratively refines the sparse recovery result. Random pilot placement is adopted according to restricted isometry property (RIP). SOMP can even perform better in lower SNR than MP, OMP and SP.

In [17] CS- based channel estimation method for MIMO-OFDM system over frequency selective fading channel is proposed. It uses orthogonal matching pursuit (OMP) for reconstruction. Also [17] satisfies the restricted isometry property (RIP) of the measurements by discrete partial Fourier transform based PSACE method. [17] Can outperform the conventional LS methods and greatly decrease the pilot overhead burden and hence improve spectrum efficiency.

Since the MP algorithms have some shortcomings, in [18] Signal Adaptive Matching Pursuit algorithm is used. In the channel of unknown sparse degrees, the algorithm can get good channel estimation performance, and reduce the complexity of the system. The computational complexity is lowered.

OFDM systems can provide high data rate with high bandwidth efficiency in wireless communication. But their performance is limited by Narrowband interference (NBI) signal. So, in [19] zero padding based compressive sensing approach is proposed to detect and mitigate the NBI in MIMO-OFDM and to analyse its performance. The performance measures show that the there is significant improvement in bit error rate (BER) after applying this approach.

In [20], a novel sparse channel estimation method using sparse cognitive matching pursuit algorithm. Compared to other compressive algorithms in the state of art, the major innovation of the SCMP sparse channel estimation method is the ability of obtaining the accurate CSI without prior information of sparsity. The proposed method has better estimation performance and lower estimation complexity.

In [21] a system with an asymmetric DAC/ADC pair and formulates OFDM channel estimation as a compressive sensing problem. The proposed system realizes high-resolution channel estimation at a low cost.

Basis Pursuit (BP) and Matching Pursuit (MP) are probably the most popular recovery algorithms in the CS literature. Whereas for BP theoretical performance guarantees are available, OMP lacks similar results. On the other hand, OMP allows a faster implementation, and simulation results even demonstrate a better recovery performance.

MP is one greedy algorithm that constructs a linear combination of matrix columns closest to the signal. Although MP can rapidly find an approximation with asymptotic convergence, its shortcoming lies in the fact that it may select the same columns several times which lowers the efficiency. Hence, OMP has been proposed as a revised MP by only using residue's orthogonal component for the next iteration. Only the component that is orthogonal with the space spanned by the previous selected columns is preserved. The shortcoming of OMP lies in its unidirectional adding new columns without removing out-dated columns. When a selection error occurs, the iteration will continue to the end without correcting them adaptively. The idea of SP is to iteratively refine S columns selection from the dictionary matrix through LS method until the stop condition is satisfied. At each step, it selects S columns rather than only one column as in MP and OMP. The subspace spanned by S columns is thus tracked down. The weak point of SP is that we should know S before the start of the algorithm. So it's necessary to extend SP to the occasion where the sparsity is unknown. The stop condition for OMP employs the threshold that equals to the noise variance, while the counterpart for SP only relies on previous iterative result. Apparently the latter is more appealing since it can iteratively refine the result. Besides, SP allows the columns to enter into as well as leave the selection set, which is the chief drawback for OMP. At each iteration, OMP always greedily selects one column vector, while SP selects several columns in batch. The possibility to correctly find one column with one selection is much lower than with batch selection.

The main advantages of sparsity-based approaches can be categorized into two parts:

Decreasing MSE: Generally, the purpose of using compressed sensing methods in solving a linear set of equations with the sparsity constraint is to achieve the Cramer Rao lower bound on MSE. In extreme cases, the structured LS estimator which knows the location of nonzero taps (support) through an oracle, and estimates their corresponding values using LS estimation is the best estimator. The MSE of this estimator is called CRB-S. However, in general, there is no information about the location of the nonzero coefficients of h at the receiver and the structural LS estimator is not realizable. Simulation results indicate that we can get close to this bound by using proper sparsity-based methods.

Reducing Overhead: Although the pilot subcarriers occupy a fraction of the spectrum, they do not convey any data. By reducing the number of pilot subcarriers, we increase the utilization efficiency of the spectrum while we may degrade the performance of the channel estimation block. By considering the sparsity of the CIR, it is possible to capture the necessary information in the frequency domain in less number of pilots. The $\ell 1$ minimization technique almost perfectly reconstructs the sparse CIR from when the number of pilots is proportional to the number of channel taps. Furthermore, the reconstruction performance is independent of the location and value of the taps; i.e., unlike the interpolation based methods, the number of required pilot subcarriers does not depend on the delay spread and degree of frequency selectivity of the channel.

2.1.3. DECISION DIRECTED CHANNEL ESTIMATION

DDCE is one of the earliest methods studied for OFDM, mainly because of its popularity in legacy systems. In the earlier studies, DDCE was applied mostly in training based systems, where one or more OFDM symbols were used as the training symbols. The main idea behind DDCE is to use the channel estimation of a previous OFDM symbol for the data detection of the current estimation, and thereafter using the newly detected data for the estimation of the current channel. Data detection can be based on hard or soft decision. Once the data at the subcarriers is detected, any methods described in the previous subsections can be used to estimate the current channel.

Although DDCE is simple, it inherently introduces two basic problems: the use of outdated channel estimates, and the assumption of correct data detection. The use of outdated channel estimates does not pose a serious issue when the channel is varying very slowly. However, when the channel starts varying faster, then the outdated channel estimates for the previous OFDM symbol are no longer valid for the use of the data detection in the current OFDM symbol. In this case, the data detection would be incorrect, so are the newly estimated channel coefficients. Hence, the error in the channel estimation and data detection build up to make the system performance unacceptable. This error propagation becomes more critical when the number of incorrect decisions increases at low SNR regions.

As a quick solution to overcome the problem related to the outdated channel estimates, the training symbols can be sent more often. The time instances at which the training symbols should be sent can be based on different criteria. Training symbols can be sent periodically where the period is predetermined for a given system. Moreover, the change in channel estimates can be monitored to determine whether channel estimation is indeed needed. As the channel varies fast over the time, the need to send the training symbols more frequently has a high penalty in terms of the overall system efficiency. In this case, training symbols can be replaced by the pilot subcarriers. Although sounds to be a good solution, the lack of reliable information about the subcarriers and the high probability of the reliable subcarriers being non-uniformly distributed over the OFDM symbol reduce the performance of this approach. By increasing the power level of the reliable subcarriers, the performance degradation can be mitigated to some extent. Another approach can be the use of prediction algorithms on the channel estimation. The channel estimated in previous OFDM blocks can be used to predict the channel in the next block. Prediction algorithms can be applied either on the channel taps or the channels at the subcarriers. The previous has the advantage that the number of variables to predict is much smaller but needs IFFT to get the channel at the subcarriers. The latter requires no transformation but it requires the prediction of more number of variables, that is, subcarriers. Besides, since the prediction is performed individually for each subcarrier, the correlation properties of the subcarriers are not utilized that result in a worse performance when compared to the prediction for the time domain channel coefficients.

Coding theory is probably one of the most widely fields applied to the data detection portion of the OFDM systems. With coding available in OFDM systems, DDCE can exploit this information to improve the data detection. The typical coding mechanisms are RS, convolution, trellis, turbo, and LPDC coding.

DDCE methods fit in systems operating in static or quasi-static channels. It particularly fits in systems in a slot transmission mode, such as wireless cellular systems. Initial channel estimation is provided with the training blocks and is then followed by tracking or prediction. Their major advantage is that they are able to provide high spectrum efficiency by using detected data as pilots.

CONCLUSION

This article provides a review on various channel estimation techniques for OFDM system and mainly focus on channel estimation based on compressive sensing. Channel estimation mainly depends on three basic blocks. These are the pilot patterns, the estimation method, and the signal detection part when combined with the channel estimation. As in many systems, each block can promise an improved performance at the cost of additional resources. Hence, the best combination of these three parameters depends on the typical application. Efficient OFDM channel estimation will drive OFDM to carry the future of wireless networking. A great opportunity for high-efficiency OFDM channel estimation is lent by the sparse nature of channel impulse response. New technique based on compressive sensing can be used for OFDM channel estimation, as it proves itself superior to existing technique. The main advantages of using CS based techniques include it decreases MSE and pilot overhead and hence improve spectrum efficiency. The comparison of different techniques is given in Table 1.

TABLE 1. Comparison of different techniques

Techniques	Merits	Demerits
LS estimation	Less computational complexity	do not utilize the long term channel statistics and hence perform worse
Transform domain technique	Less computational complexity Decreases MSE	Their performance are heavily dependent on the CIR tap locations, an inaccurate assumption of CIR tap locations can degrade any of the transform domain techniques drastically. Not suitable for practical systems such as WLAN and WiMAX
LMMSE estimation	Improved performance – by using information like SNR and other channel statics. Minimize the MSE.	higher computational complexity
Compressive sensing	Decrease MSE Reduces pilot overhead	
DDCE	Simple and have less computational complexity.	the use of outdated channel estimates the assumption of correct data detection error propagation

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