An Efficient Blind Modulation Detection Algorithm for Adaptive OFDM Systems

Sharath B. Reddy, Tevfik Yücek and Hüseyin Arslan
Department of Electrical Engineering, University of South Florida
4202 E. Fowler Avenue, ENB-118, Tampa, FL, 33620
{sbreddy, yucek, arslan}@eng.usf.edu

***Abstract*— Adaptive modulation is a method to increase the data capacity, throughput and efficiency of time division duplexed wireless communication systems. In adaptive modulation, the transmitter continually monitors the dynamic channel and adjusts the transmission parameters such as modulation order, coding rate *etc.* accordingly. Blind modulation detection schemes play an important role in adaptive systems to eliminate the need for transmitting modulation information, thereby increasing spectral efficiency. In this paper, an improved statistical blind modulation detection method based on the Kullback-Leibler distance is proposed for OFDM based wireless communication systems. Simulation results show that this blind modulation detection algorithm outperforms similar previously proposed algorithms.**

I. Introduction

Orthogonal Frequency Division Multiplexing (OFDM) has been recognized as one of the most effective techniques to improve data capacity and is a strong candidate for use in fourth generation wireless communication systems. The prospect of multipath delay spread mitigation is one of the most compelling reasons to choose OFDM for mobile wireless channels. Adaptive modulation is a method to increase the data capacity, throughput and efficiency of time division duplexed (TDD) wireless communication systems. The three steps that entail the process of adaptation are channel estimation, parameter adaptation and signaling/blind detection of the modified parameters. The focus of this paper is restricted to reliable blind modulation detection schemes. An improved statistical blind modulation detection method based on the Kullback-Leibler distance is proposed for OFDM based wireless communication systems.

The paper is organized as follows. Section II introduces the concept of adaptive modulation. Section III describes blind modulation detection with a summary of prior literature on this topic. This is followed by the description of the OFDM system model in Section IV. Section V introduces the proposed algorithm for blind modulation detection. Finally, a synopsis of the simulation results are presented in Section VI followed by concluding remarks.

II. Adaptive Modulation

In adaptive modulation, the transmitter continually monitors the dynamic channel and adjusts the transmission parameters accordingly to maximize efficiency [1]. Monitoring is done in the reverse channel, and the adaptation is applied in the forward channel based on the observed channel conditions, assuming the channel to be constant during forward and backward link transmissions.

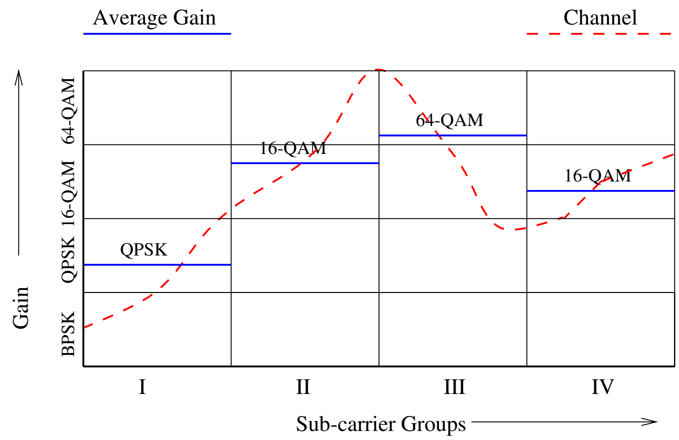

Fig. 1. Modulation mode selection based on perceived channel quality.

Adaptive OFDM systems have the capability of mitigating the issue of a slowly varying channel since channel variation can be exploited both in time and frequency domain. Slowly varying reciprocal channels have to be assumed since adaptation assumes that the channel does not change between estimation and parameter adaptation. If the channel varies rapidly, then the predicted values might be inaccurate, which would lead to choosing the wrong set of parameters [2].

The concept of varying the number of modulation levels according to instantaneous channel conditions was introduced in [3]. It was observed that QAM transmissions over Rayleigh fading channels resulted in error bursts due to deep fades occurring in certain sub-carriers. A possible solution to this would be to increase the transmission power, which is not feasible in certain cases. Also, increasing the power would cause co-channel interference. Instead, the number of modulation levels are varied according to the integrity of the channel. When the received signal is not in fade, the modulation order is increased to take full advantage of the channel condition and maximize throughput. As the received signal fades, the modulation level is decreased to a level so as to provide an acceptable bit error rate (BER). Since adaptation in every sub-carrier would be extremely complicated, often sub-carriers are grouped together, and adaptation is performed on the entire sub-carrier group. This is termed as sub-band adaptive modulation and is illustrated in Fig. 1, which shows the different modulations used at different sub-carrier groups based on the channel conditions. Sometimes, an entire group of sub-carriers can be excluded from any data transmission because the signal level at the receiver might be lower than the noise floor, thereby making detection impossible. The goal of adaptive modulation is to choose the appropriate modulation mode for transmission in each sub-carrier, in order to achieve a good tradeoff between throughput and overall BER.

The aim here is to fully exploit the time-variant Shannonian capacity of the fading channel. This idea has been extended in [4] and [5] to maximize system performance over Rayleigh fading channels. Adaptive systems are not limited to only varying the modulation schemes alone, but also other parameters such as coding rate, symbol rate *etc.* can be adapted depending on the channel reliability information as mentioned in [6].

Modulation scheme selection algorithms for adaptive systems are based on different criteria such as BER constraints, constant throughput or sometimes both, depending on the intended application. Various modulation selection algorithms have been proposed recently, which use different criteria to decide between modulation schemes based on channel conditions [7], [8].

III. Blind Modulation Detection

To detect the transmitted symbols correctly, the receiver has to know which modulation is being used at the transmitter. Two methods, namely parameter signaling or blind detection, can be employed. Parameter signaling is where the modulation information is embedded within the transmitted data symbols. This has the obvious disadvantage of reducing data throughput due to the signaling symbols. An alternative would be blind detection of the modulation mode of received symbols.

Blind modulation detection schemes are used to minimize the loss of useful data bandwidth by estimating the modulation schemes used at the transmitter without explicit signaling. This has the advantage of increased spectral efficiency and improved throughput over traditional signaling schemes. Also, efficient blind modulation detection schemes provide insight into the channel and noise characteristics of the propagation medium in adaptive modulation systems.

Blind modulation detection has been traditionally approached in two ways, namely pattern recognition and decision theoretic approaches [9]. In statistical pattern recognition methods, several recognized pattern recognition algorithms such as Fuzzy C-means clustering [10] have been proposed and tested to perform well, provided that there are a relatively large number of samples available to make a decision. Within the scope of adaptive OFDM systems, there are no algorithms in literature to the authors' knowledge which follow a pattern recognition approach till date, primarily because it is desired that detection be done in real time with a low number of samples. A large sample size would require memory, and hence signaling is considered a better alternative as opposed to using the pattern recognition approach.

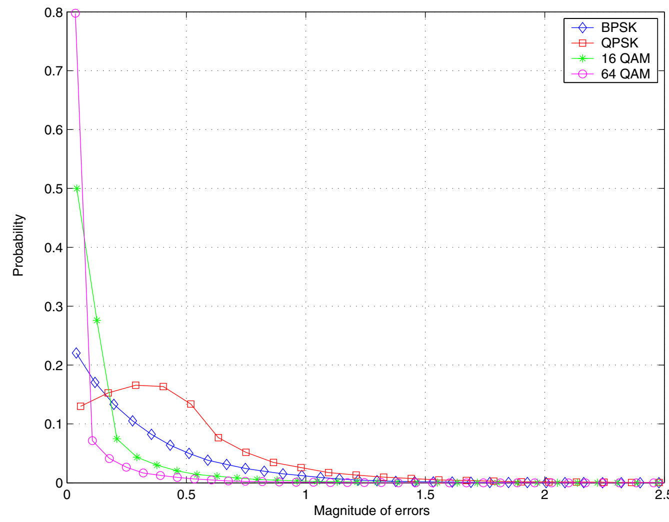

Fig. 2. Probability distribution of errors with BPSK at channel SNR = 5dB.

The objective of blind modulation detection is to determine the type of modulation used with the information conveyed by the least possible number of received samples. The only empirical data provided by the received noisy samples is the distance to the closest legitimate constellation point of all the used modulation schemes. In other words, given a noisy sample, there would be M errors where M is the number of modulation schemes used. Therefore, the objective is to make use of the distribution of these empirical data or errors to make a statistical inference of the type of modulation used.

Two methods with reference to blind modulation detection for adaptive OFDM systems are proposed in [11], which are based on the decision theoretic approach. In the first method, the mean Euclidean distance between the received samples and all the closest legitimate constellation points of all possible modulation schemes are calculated. The average Euclidean distance for different hypotheses can be calculated as,

$$e_m = \frac{\sum_s |R_s - \hat{R}_{s,m}|^2}{S} \quad m = BPSK,\ QPSK\ etc. \quad (1)$$

where R is the received sample, $\hat{R}$ is the hypothesis of the received sample, m is the index of the modulation, and S is the number of samples used for averaging. The scheme which minimizes the average Euclidean distance e is chosen for demodulation. However, there is always a bias towards the higher order modulation schemes irrespective of the actual modulation used. The reason is that there are more number of closer legitimate points for higher modulation schemes which would yield lower errors. This is illustrated in Fig. 2, which shows the distributions of the errors for different modulation schemes at 5dB signal-to-noise ratio (SNR) when BPSK is used for transmission. There is a bias towards 64-QAM, *i.e.* most of the time 64-QAM is selected as the modulation scheme although BPSK is used at the transmitter end. This

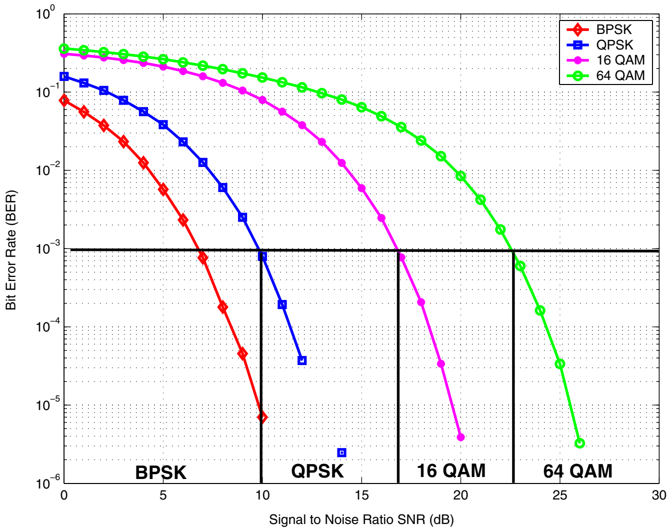

Fig. 3. SNR bounds within which different modulation schemes are used.

problem exists because 64-QAM has the highest probability of yielding the lowest error. Reliable detection is possible only for SNR values of 18 dB and over (see Fig. 6). The second method given in [11] makes use of convolutional encoding with Viterbi decoding to estimate the modulation scheme. However, there is a high degree of computational complexity involved and this method entails the use of coding, which is out of the scope of this paper.

Instead of using only the error information provided by the received noisy samples, the unique distribution of these errors for each SNR and modulation scheme is taken into account. This *a priori* information, *i.e.* probability distribution of errors, is used to determine the transmitted SNR in the proposed algorithm. For a given SNR and modulation scheme, the probability distribution function (PDF) of the errors for every modulation hypothesis is unique and can be obtained ahead of time by simulation or actual drive test measurements. The received distribution and the known distributions are compared to find the closest match, which would give the SNR at the transmitter.

We assume that the modulation schemes are chosen such that a maximum BER of 10^{-3} is obtained. The SNR bounds within which different schemes are used are shown in Fig. 3. In this case, different modulation schemes are selected based on the estimated SNR at the transmitter to provide desired BER performance. Hence if we assume that the SNRs at the transmitter and receiver are the same, then calculation of the transmitted SNR at the receiver would give us information about the modulation scheme used. In other words, blind modulation detection would be the same as SNR estimation in this case, provided the bounds within which each scheme is used is known at the transmitter and receiver ends.

IV. OFDM System Model

OFDM converts serial data stream into parallel blocks of size N and modulates these blocks using IDFT. Time domain samples can be calculated as

$$\begin{aligned} x(n) &= IDFT\{X(k)\} \\ &= \sum_{k=0}^{N-1} X(k) e^{j2\pi nk/N} \qquad 0 \le n \le N-1 \ , \end{aligned} \quad (2)$$

where $X(k)$ is the transmitted symbol on the kth sub-carrier. Time domain signal is cyclically extended to avoid residual ISI from the previous OFDM symbols.

At the receiver, the signal is received along with noise. After synchronization, down sampling, and removal of cyclic prefix, the baseband model of the received samples can be written as

$$Y(k) = H(k)X(k) + n_k \ , \quad (3)$$

where $Y(k)$ is the received symbol on the kth sub-carrier, $H(k)$ is the frequency response of the channel on the same sub-carrier, and n_k is the additive Gaussian noise sample with mean zero and variance of σ_n^2.

V. Kullback-Leibler Distance Algorithm

We begin by introducing the Kullback-Leibler or K-L distance in its simplest terms. Conceptually, the K-L distance is defined as a directed distance between any two probability distribution functions, f and g [12]. In the forthcoming discussions, the probability distribution of the errors from the received symbols will be referred to as f and the approximating model, as g. The directed distance between the two distributions is a measure of the dissimilarity between them, and should not be confused with simple Euclidean distance. The directed distance from f to g is not the same as that from g to f. The basis of K-L distance is both deep and fundamental and is a rudimentary quantity in information theory, and is the basis for model selection in conjunction with likelihood inference.

The expression for the K-L distance between two discrete probability distributions is,

$$I(f,g) = \sum_{i=1}^{L} p_i \ \log \frac{p_i}{\pi_i} \quad (4)$$

where the true probability of the i^{th} outcome is given by p_i, and π_1 to π_L correspond to the elements of the approximating probability distribution. Both, $\sum p_i$ and $\sum \pi_i$ are equal to 1. Hence, here f and g correspond to the p_i and π_i, respectively. Simply put, $I(f,g)$ is the information lost when g is used to approximate f.

The concept of model approximation is well suited to blind modulation detection. In adaptive modulation, different modulation schemes are used between specific SNR bounds to yield optimum performance. If PDF approximation can be used to determine the SNR at the transmitter, then the modulation scheme can be estimated easily. Let us assume that for a set of K SNRs, the probability distributions of the errors, *i.e.* the PDFs $g_1 \ldots g_K$ for K SNRs, are completely known. Then, from a set of received noisy symbols, it is possible to calculate the distribution of the errors, *i.e.* model f, and

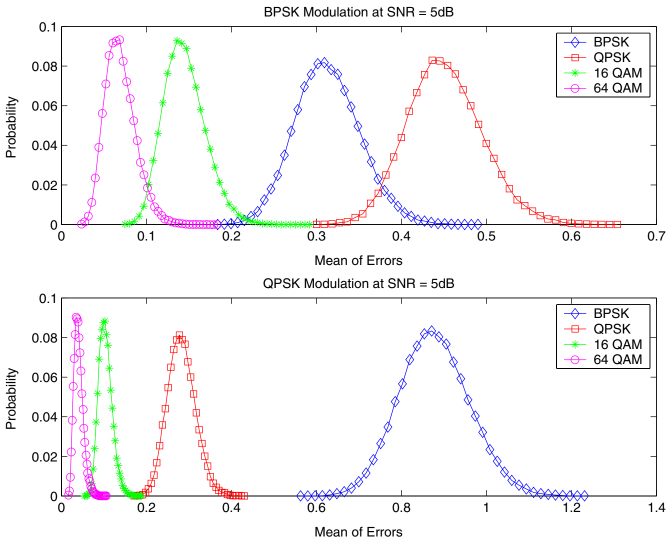

Fig. 4. Distribution of the first order statistics of the errors for different modulation schemes when BPSK and QPSK are used at 5dB SNR

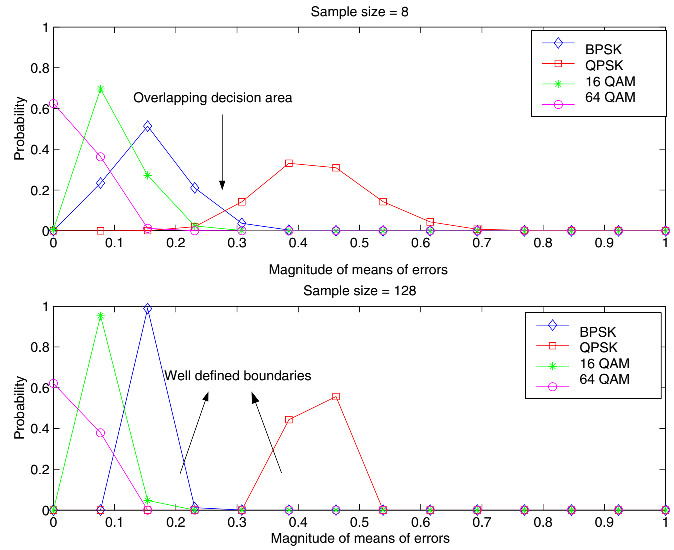

Fig. 5. Effect of the number of samples on the first order statistics of the probability distribution of errors.

estimate the K-L distances to all the approximating PDFs g_1 to g_K, which were obtained ahead of time. By minimizing the K-L distance, we obtain the transmitted SNR and hence the modulation scheme.

There are other metrics such as mean-squared-error MSE between the elements of f and g to do the same operation which can be calculated as follows,

$$MSE_k = \sum_{i=1}^{L} (p_i - \pi_{k,i})^2 \qquad 1 \leq k \leq K \ . \tag{5}$$

However, only a simple measure of the distance and not a weighted directed distance is obtained. This is the reason K-L distance is well suited to this SNR estimation approach of blind modulation detection. Two sets of distributions may have the same MSE, but may have been transmitted at different SNRs.

Ideally, we would like to know all the parameters associated with the model f. This would require a large sample size, which is not practically possible. Instead, the first and second order statistics of the distributions f and g can be used to eliminate the large sample requirement. This paper will focus on using the first order statistics, *i.e.* the means of the distributions of errors, of f and g. The first order statistics of both probability distributions have unique distributions also, as illustrated in Fig. 4. A large sample size magnifies the separation of the distributions of the first order statistics of errors as seen in Fig. 5. Notice that, as the sample size increases, the decision regions become narrower and the distinction between the modulation schemes become sharper. This implies that, as the number of samples available for averaging increases, incorrect decisions are less likely to occur at the decision boundaries of adjacent modulation schemes. It is observed from simulation results that for sample sizes of 64 and above, the K-L algorithm performs without any errors.

With the *a priori* knowledge of the first order statistics of both distributions, a comparison will be made between decisions based on simple Euclidean distance as given by (1), the mean square error, and direction oriented K-L distance between the first order statistics of the distributions f and g. The latter two methods use *a priori* information of the first order statistics of both probability distributions.

VI. Results

To verify the proposed algorithm, an OFDM system with 64 sub-carriers is simulated. Four different modulation schemes, namely BPSK, QPSK, 16-QAM and 64-QAM, are used for transmission, based on the observed channel conditions. SNR bounds for each modulation scheme is defined by the limits within which a 10^{-3} BER can be achieved, as shown in Fig. 3. The modulation schemes are assumed to change gradually one level at a time in a slowly varying channel. For simulations, perfect channel knowledge is assumed. Three methods namely the Euclidean distance, MSE and K-L distance minimization are compared and contrasted, and the results are presented in Fig. 6.

It is seen that the algorithm which minimizes the Euclidean distance between the mean errors performs well only above channel SNRs of 18 dB. The MSE algorithm which uses *a priori* knowledge of the first order statistics of the distributions has sporadic errors. This is expected because the distributions do not have a specific linear pattern associated with them. The K-L algorithm is observed to perform without any errors when the sample size is 64.

The results in Fig. 6 are obtained for cases where the noise variance at the transmitter and the receiver are the same. In practical cases, this assumption may not be valid since the transmitter and receiver would be suffering from different noise variance levels. The variance of the noise at the receiver

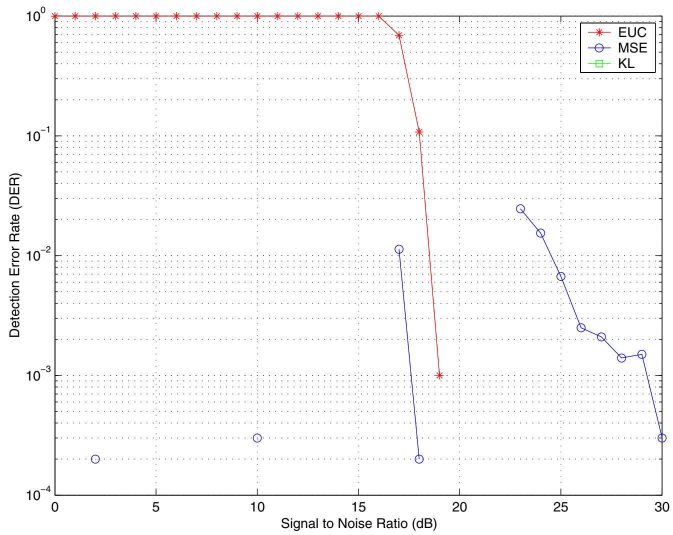

Fig. 6. Detection error rate comparison between the Euclidean, MSE and K-L algorithms. No incorrect decisions with K-L algorithm for sample size of 64 and equal noise variance at the transmitter and receiver.

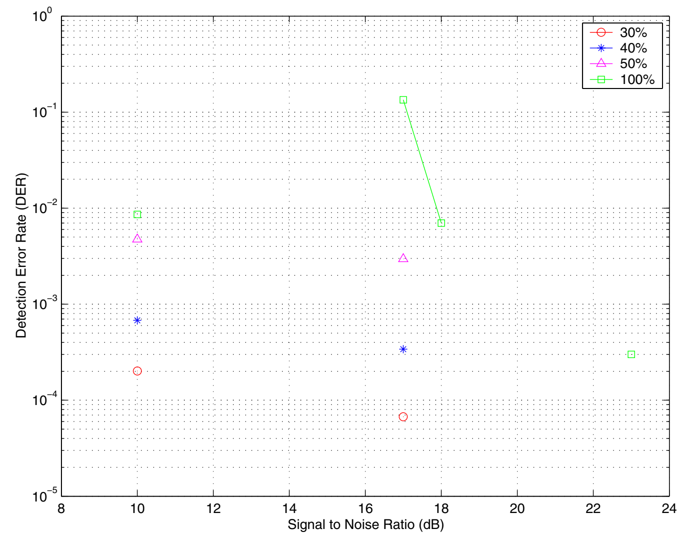

Fig. 7. Detection error rate of K-L algorithm with different levels of noise variance mismatch between transmitter and receiver expressed in percentage.

is modeled as,

$$\sigma^2_{Rx} = \sigma^2_{Tx}(1 \pm \zeta) \tag{6}$$

where σ^2_{Rx} and σ^2_{Tx} are the noise variances at the receiver and transmitter respectively and ζ is the term that represents the noise variance mismatch between transmitter and receiver. The robustness of the algorithm is tested for noise variance mismatch of 30%, 50%, 70% and 100% between transmitter and receiver, and the results are presented in Fig. 7. It is found that errors are concentrated in the modulation transition regions at noise variance mismatch levels of 30% and above. This is expected because errors in the SNR estimation within the bounds of each modulation scheme will not affect the decision error rate as much as SNR estimation errors at the modulation transition regions does.

VII. Conclusion

In this paper, an improved decision theoretic blind modulation detection method based on the Kullback-Leibler distance is proposed for OFDM based wireless communication systems. The algorithm is shown to perform exceptionally well with a sample size of 64, which proves that this technique is suitable for adaptive as well as sub-band adaptive modulation systems depending on the sub-carrier size.

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