Efficacies of Selected Blind Modulation Type Detection Methods for Adaptive OFDM Systems

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***Abstract* - Adaptive modulation techniques have been proposed to optimise Shannon's channel capacity in orthogonal frequency division multiplexing (OFDM) system. By adapting the modulation type (effectively changing the number of bits per symbol) at the transmitter end one could improve the bit error rate (BER) during transmission at designated SNR. Blind detection of the transmitted modulation type is desirable to optimise the band-width available. This in turn implies the need for an intelligent modulation classification engine at the receiver end. In this work, we review and investigate two well-known modulation classifiers, as well as propose a new candidate classifier based on up to sixth order statistics.**

I. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) has been proposed as the candidate modulation system for achieving high data rates in multi-path fading wireless communication environment. Its counterpart in wired communication is the discrete multitone (DMT) which was implemented in ADSL modem system. An example standard of OFDM is the IEEE 802.11a where the data throughput rate ranges from 6 Mbps to 48 Mbps, depending on which modulation type (BPSK, QPSK, 16QAM or 64QAM) is used. In essence, OFDM is a multi-carrier modulation scheme in which the data symbols are transmitted in parallel using multiple carrier frequencies as in the case of frequency modulation (FM). Instead of deploying multiple carriers, this could be efficiently implemented using inverse discrete time Fourier transform (IDFT), and then transmitted using a higher frequency carrier. It is believed that OFDM system provides stronger resilience against inter-symbol interference (ISI) and multi-path fading [8].

Adaptive modulation for OFDM system [9] was first proposed by Steele and Webb [1] to exploit the time-variant Shannon's channel capacity of fading narrowband channel. The main motivation is to mitigate the loss of system throughput (as a result of omitting subcarriers with severe fades) by employing higher order modulation types on subcarriers with high signal to noise ratio (SNR). When the number of subcarriers is large, one would normally consider the average SNR of a neighborhood of subcarriers and employ the same modulation type for these subcarriers. This is referred to as sub-band adaptive modulation.

There are three main steps in adaptive modulation: 1) channel quality estimation, 2) modulation type adaptation for next transmission, and 3) blind modulation type detection of the employed modulation type at the receiver end. In this paper, we focus on the third step and assume that the channel information is available through estimation, possibly through a duplex communication link. Numerous techniques have been proposed for single carrier system, e.g. [2 – 5, 8 – 9]. In this work, we compare two well known modulation classifiers (MC) - the maximum likelihood (ML) MC [2, 6] and the higher order statistics (HOS) based hierarchical MC [3], adapted in the OFDM's setting. In addition, we also propose a new candidate MC based on up to sixth order statistics.

In the next section we describe the system model for our investigations. Following this are the sections on maximum likelihood classification and hierarchical classification using up to fourth order statistics. Next we present investigations using sixth order statistics and propose a candidate method for sub-band OFDM modulation classification. Conclusions follow after this.

II. SYSTEM MODEL

In OFDM, a serial stream of data is converted into parallel blocks of size N which we represents in vector form, $\mathbf{X} = [X_1 X_2 X_3 \ldots X_N]$. Each symbol is mapped to one of the candidate modulation types, m_i. In this work, we consider four modulation candidate types only, namely BPSK, QPSK 16QAM and 64QAM. $\mathbf{X}$ is then transformed using N-point inverse discrete Fourier transform (IDFT), to give the time domain sequence, x(n), [6, 7]:

$$\begin{aligned} x(n) &= \text{IDFT}\{\mathbf{X}\} \\ &= \sum_{k=0}^{N-1} X_k \exp\left(\frac{j2\pi nk}{N}\right) \quad 0 \le n \le (N\text{-}1) \end{aligned} \tag{1}$$

Before transmission, x(n) is typically extended cyclically, or zero-padded, to avoid ISI from previous symbol, filtered, converted to analogue form, and transmitted through antenna over a wireless channel.

At the receiver, the transmitted signal is corrupted with noise. After pre-processing (synchronization, down sampling, and cyclic extension removal), the baseband model of the received symbols is written as:

$$Y_k = H_k X_k + V_k \tag{2}$$

where H_k and V_k is the subcarriers' frequency response and complex additive white and Gaussian noise in frequency domain. Without loss of generality, we can assume v_k to be of zero mean and variance of σ^2. It is also customary to assume that the received symbols are i.i.d. and normalized to unit power i.e.:

$$E\{|Y_k|^2\} = \frac{1}{N}\sum_{k=1}^{N}|Y_k|^2 = 1 \tag{3}$$

III. Maximum Likelihood Classification

Let m_i and M_i denotes the possible modulation type and the total number of possible symbols with i = *1, 2, 3* and *4* corresponding to the set of {BPSK, QPSK, 16QAM, 64QAM}. The transmitted symbol, X_i, can take one of the M_i possible complex symbols, a_j, j $\in$ 1, 2, …, M_i. The normalized constellations of QPSK, 16QAM and 64QAM are depicted in Figure 1.

Given a sub-group of received symbols, **G** = [Y_1, Y_2 … Y_L], we can calculate the likelihood of the received group belonging to the modulation type, m_i, using the following [6]:

$$P(\mathbf{G} \mid m_i) = \prod_{n=1}^{L} P(Y_n \mid m_i) = \prod_{n=1}^{L}\left(\frac{1}{M_i\sqrt{2\pi\sigma^2}}\sum_{j}^{M_i}\exp\left(-\frac{|Y_n - \hat{H}_n a_j^i|^2}{2\sigma^2}\right)\right) \tag{4}$$

where a_j^i refers to the symbol j in modulation type i and L denotes the number of carriers in the subband. Usually, it is more practical to take the natural logarithm of (4). As it is a monotonic function, taking the maximum of the logarithm achieves the same result as taking the maximum of likelihood function:

$$\ln P(\mathbf{G} \mid m_i) = \sum_{n=1}^{L}\left(\ln\frac{1}{M_i}\sum_{j}^{M_i}\exp\left(-\frac{|Y_n - \hat{H}_n a_j^i|^2}{2\sigma^2}\right)\right) \tag{5}$$

Note we also drop the constant term resulting from (4) in (5).

We carried out computer experiments in MATLAB environment to test the ML MC using the said modulation types. The numbers of carriers was set to 512 carriers and the probability of correct classification, P_c was calculated based on 30 trials. The result was then plotted in Figure 2.

The ML Modulation Classification (MC) algorithm gives the theoretical optimum results when the SNR is high and known to users. However, as it can be deduced from Equations (4) and (5), the ML MC has a high computational requirement. In the case where SNR is not known *a priori*, we have to choose a suitable SNR estimation algorithm although this requirement can be somewhat relaxed as shown in [4, 5]. The other major drawback for ML MC is that it tends to favour highly dense modulation type (64QAM in our example) in low SNR region as shown in Figure 2.

IV. Hierarchical Classification Using Higher Order Stastics

Swami and Saddler [3] proposed a simple but efficient hierarchical classifier for a Single Carrier Classification in [3] using fourth order cumulants as feature sets. The two features, C_{40} and C_{42}, could be calculated based on the following equations. We adopt the notation as in the previous section for uniformity.

$$C_{40} = \frac{1}{L}\sum_{n=1}^{L} Y_n^4 - 3\hat{C}_{20}^{\,2} \tag{6}$$

$$C_{42} = \frac{1}{L}\sum_{n=1}^{L}|Y_n|^4 - \left|\hat{C}_{20}\right|^2 - 2\hat{C}_{21} \tag{7}$$

with C_{20} and C_{21} define as follows:

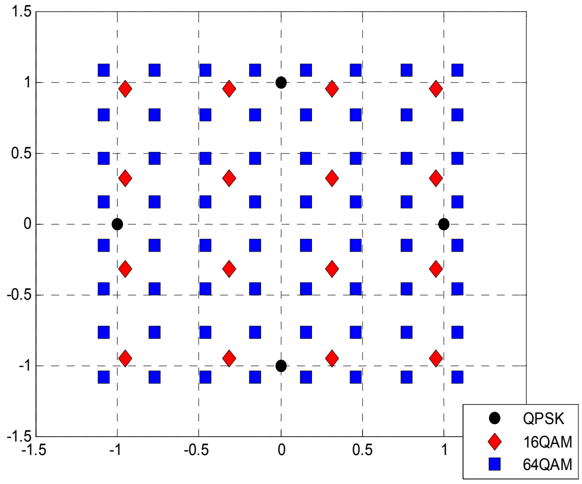

Figure 1 Constellation diagrams of QPSK, 16QAM, and 64QAM.

$$C_{20} = \frac{1}{L}\sum_{n=1}^{L} Y_n^2 \tag{8}$$

$$C_{21} = \frac{1}{L}\sum_{n=1}^{L}|Y_n|^2 \tag{9}$$

We have adapted their algorithm to our chosen modulation classification problem using a set threshold values chosen based on the theoretical value shown in Table I. These theoretical values are calculated using the ideal noise-free constellation.

From Table I, it appears that the values of C40 and C42 are the same for four modulation types that we have chosen in our study. Therefore one in theory could choose either. We have chosen values of C42 in this work as

$C42 \le -1.5 \rightarrow$ BPSK,

$-1.5 < C42 \le -0.84 \rightarrow$ QPSK

$-0.84 < C42 \le -0.6496 \rightarrow$ 16QAM

$-0.6496 < C42 \le -0.5 \rightarrow$ 64QAM

For ease of reference, we refer the above algorithm as HOS (C42) MC.

We carried out an identical experimental setup as with the previous section and observed the following from the result shown in Figure 3:

a. The HOS (C42) MC is much faster than ML MC. We await further numerical results to validate our observation.

b. Unlike the ML MC, the HOS (C42) MC has no bias towards dense modulation at low SNR.

c. On the contrary, the HOS (C42) MC shows confusion between 16QAM and 64QAM as the gap between the two theoretical values are too close.

d. Even at 10 dB SNR, it is difficult to distinguish the 16QAM and 64QAM using C42.

TABLE I

THEORETICAL NOISE FREE VALUE FOR C40 & C42

Features	**BPSK**	**QPSK**	**16QAM**	**64QAM**
C40	-2.000	-1.000	-0.680	-0.619
C42	-2.000	-1.000	-0.680	-0.619

TABLE II

THEORETICAL NOISE FREE VALUE FOR C60 & C63

Features	**BPSK**	**QPSK**	**16QAM**	**64QAM**
C60	-16.000	0.000	0.000	0.000
C63	16.000	4.000	2.080	1.797

TABLE III

CONFUSION MATRIX AT DIFFERENT SETTINGS OF L.

Mod. Type	P_c (%) at SNR = 10 dB								
	L = 2046			L = 1024			L = 512		
	1	2	3	1	2	3	1	2	3
1	100	0	0	100	0	0	100	0	0
2	0	100	0	0	100	0	0	100	0
3	0	0	100	0	0	100	0	0	100

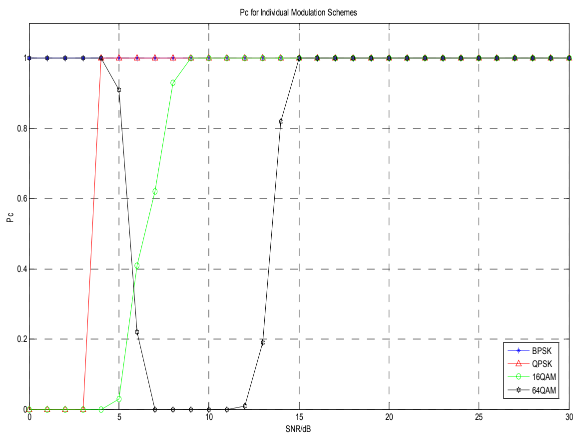

Figure 2 Performance of the ML MC depicting problems in biasing behavior for 64QAM at low SNRs.

The above observations have alerted us that C42 is not sufficient for practical modulation classification problem. In the next section, we investigate the possibility of using a set of sixth order cumulants as features for our modulation classification problem.

V. 6TH ORDER CUMULANTS

As with the calculation of the fourth order cumulants, the sixth order cumulants can be calculated using a set of formulae. Here, we are interested only in two particular sixth order cumulants, namely C60 and C63. These can be calculated as follows:

$$C_{60} = \frac{1}{L}\sum_{n=1}^{L} Y_n^{\,6} - 15C_{20}M_{40} + 30C_{20}^{3} \tag{10}$$

$$C_{63} = \frac{1}{L}\sum_{n=1}^{L} Y_n^{\,3} Y_n^{*3} - 9C_{42}C_{21} - 6C_{21}^{3} \tag{11}$$

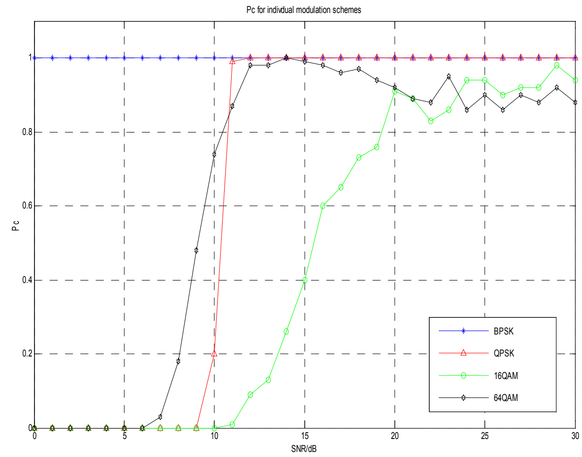

Figure 3 Performance of the HOS (C42) MC for individual modulation schemes, depicting problems for 16QAM and 64QAM even at high SNRs.

where $M_{40} = \frac{1}{L}\sum_{n=1}^{L} Y_n^{\,4}$ and * denotes the complex conjugate. Using Equations (10) and (11), we calculated and recorded the theoretical noise free value in Table II.

From the above values, it is evident that C63 provides a bigger gap between 16QAM and 64QAM, bearing in mind that these are normalized values. We have also performed a Monte Carlo analysis on the effect of SNR on the expected values of C63 and the result is as depicted in Figure 4. It is also evident from the Figure that the feature value is stable above 10 dB SNR.

Once again, we repeated the computer experiments using the sixth order cumulants by adopting the following thresholds. We refer hereafter this algorithm as HOS (C63) MC.

C63 > 6.0 → BPSK,
6.0 >= C63 > 2.75 → QPSK
2.75 >= C63 → 16QAM/64QAM

In this preliminary study, we have focussed our interest in the stability of the feature at 10 dB SNR. We have also grouped 16QAM and 64QAM as one category for this preliminary study.

Table III shows the confusion matrices at three different number of carriers, L = 2048, 1024, and 512. Regardless of L, the HOS (C63) MC achieves P_c of 100% in all modulation types.

These preliminary results give a strong indication that C63 could be a better discriminating feature than C42 in our selected modulation classification task. We await further experimental result to make final conclusion about the performance of HOS (C63) MC.

VI. CONCLUSIONS

In this paper, we have proposed the use of up to sixth order cumulants for a candidate method for sub-band OFDM modulation classification. Furthermore we presented and investigated three digital modulation classifiers for the application in blind modulation detection stage of adaptive OFDM modulation. These were namely the ML MC, the HOS (C42) MC and the HOS (C63) MC. The ML MC provides the optimum performance when the SNR is known but requires high computational requirement. This requirement causes ML MC to be less attractive when implementing in realistic applications. The two HOS based hierarchical classification methods could be easily implemented but care must be taken in selection of discriminating feature(s). The HOS (C63) MC exhibits good potential as a candidate method for adaptive sub-band ODFM modulation classification.

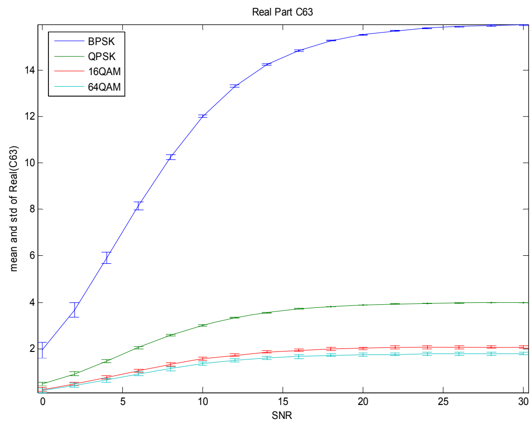

Figure 4 Mean and variance of Re{C63} plotted against SNRs.

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