An Aside on Autonomous Modulation Classification for SDR

Clarence Weston, **James E. Whitney**, **II**, **Richard Carr**
Morgan State University
Baltimore MD, USA
cweston_@hotmail.com, james.whitney@morgan.edu, carr.richard@gmail.com

Abstract – *There has been a rapid increase in interest in software defined radio (SDR) techniques in the past decade. Much of the interest stems from the applicability of efficiently using the allocated frequency spectrum for digital communication purposes, dynamically changing a modulation scheme for enhanced security or interference rejection, and the availability of modestly priced, high-speed digital signal processors that were unobtainable just a few years ago. With the advent of these needs and technologies, algorithms have been developed in order to autonomously classify a received modulated signal. This paper serves as a commentary offering a general overview on the topic of Autonomous Modulation Classification (AMC) techniques. Several current algorithms that have been proposed for AMC are also described, while making inferences to their computational complexity upon implementation.*

Keywords: Autonomous Modulation Classification, Cognitive Radio, Space Communications, Software Defined Radio, SDR.

1 Introduction

A software-defined radio is a radio communication device that mimics the traditionally used hardware components typically found in a communication receiver via programmable hardware, and software algorithms. A few advantages of using software defined radios include added flexibility, reprogramming capabilities, and dynamic configuration. The reprogramming capabilities of software defined radios provide for useful service and deployment long after a traditional radio would be rendered obsolete. Because of this, the possibility of Autonomous Modulation Classification with a software-defined radio (SDR) has many positive implications in the digital communications area. However, with the added advantages of using SDR technologies there have also been challenges in algorithm development as well as implementation issues.

2 Background

Although there are numbers of algorithms proposed for Autonomous Modulation Classification (AMC), it is important to note that all of the proposed algorithms can be classified as either likelihood based (LB) classification techniques or feature based (FB) classification techniques. It is important to make a clear distinction in the type of modulation classifier in order to quantify a classifier's performance and also the possibility of enhancing the classifier's performance if needed.

A likelihood based solution is optimal in the sense that it minimizes the probability of false alarm. In forming a likelihood classifier, it is necessary to assume a mathematical model for the received waveform and to parameterize a distribution by the received signal characteristics. To a large extent most likelihood classification techniques rely on the maximum likelihood (ML) ratio methodology although some algorithms exist that yield closed form solutions for an optimal classifier. Maximum likelihood ratio classifiers are known to be asymptotically optimal in high signal-to-noise ratio (SNR) conditions or when the data record used for processing becomes 'long'.

A feature based classifier, however, makes no claims to be optimal in any sense. Its main attractiveness stems from the reduced computational complexity as compared with the implementation of ML classifiers. The features used in feature based classifier algorithms for autonomous modulation classification are usually chosen in an ad hoc way. Once a feature is chosen to decipher the modulation scheme, then correlation, statistical parameters, or other threshold techniques are used to measure the extracted feature from a received signal against a known template feature and finally a decision is made classifying the modulation scheme.

3 Methods

Several algorithms exist by which a software defined radio can autonomously classify a modulation type. In a conventional radio, a transmitter and receiver are cooperative, agreeing on modulation type and many other transmission parameters prior to the transmitter sending data to the receiver. However, in many applications, such as cellular, deep space communications, and some military privacy communication applications, there is a need for a transmitter to change its modulation type dynamically. Therefore a SDR on the receive side must have the ability to autonomously detect the dynamically changing modulation type. Since modulation is the process that an information bearing signal is embedded into a carrier frequency more suitable for channel transmission, it is essential that a SDR have the capabilities of identifying the type of information content embedded in the received signal without prior knowledge of the transmitted modulation scheme. Information is generally embedded into a carrier by modifying the amplitude, phase or frequency of the carrier signal with properties of the information bearing signal. This paper addresses autonomous modulation detection algorithms in which the information bearing signal is embedded into the phase of the carrier signal. This paper is not intended to be an introduction to SDR or modulation theory. For a more introductory treatment of modulation techniques or general communication theory, see [1].

3.1 DFT of Phase Histogram

One feature based classifier algorithm to autonomously classify m-Phase Shift Key (m-PSK) modulation schemes utilizes the Discrete Fourier Transform (DFT) of the phase histogram [2]. The methodology makes use of the fact that with a useful PSK modulation scheme, having collected a large number of symbols, the difference in phase from symbol to symbol would be expected to vary in increments of the m-PSK modulation scheme used. A symbol in this sense represents a mapping of information carrying capacity to the total amount of discernable phase states that a received waveform is expected to have. If the units of information capacity are chosen to be in 'bits', the number of bits (per unit time) that can be transmitted in a symbol set of size M would be $\log_2(M)$ bits. Hence there is an inherent tradeoff between having the ability to place symbols very close together in order to maximize the information carrying capacity of a signal, and the ability to keep the phase spacing between symbols large enough for a detector to discern different phase states adequately. Thus, the phase increment spacing is the classification feature for this classification scheme.

The algorithm flow is illustrated in Figure 1. Although the authors did not explicitly denote hardware requirements for full implementation of the algorithm, assumptions can be made of low complexity from the block diagram in Figure 1. A phase detector and an additional algorithm must be used to construct a histogram of the collected phase data. A fast Fourier transform (FFT) block is used and the maximum magnitude of the FFT bins is taken to be the phase increment spacing that corresponds to most of the symbols in the received waveform. The algorithm chooses the index of that bin as the current m-PSK modulation scheme in use.

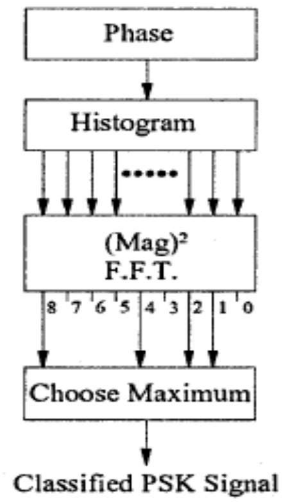

Figure 1. DFT/Phase-Histogram Processing Flow.

It is important to note that the authors make no claims of the classifier being optimal; instead, they propose the scheme to be robust and work very well in low SNR environments. In another algorithm [3], a hybrid of this technique is used to implement a classifier for quadrature amplitude modulation (QAM) signals.

3.2 Maximum Likelihood Modulation Classification for PSK/QAM

A maximum likelihood classification technique for PSK and QAM modulation types has also been proposed [4]. The method entails correlating an estimate of the transmitted symbol (noisy waveform) with all the possible symbols of all the possible sets of symbols of the candidate modulation types requiring classification. This operation is performed over a block of data and a given number of symbols. The assumption is made that all other unknown parameters, i.e., symbol rate, carrier frequency, carrier phase, pulse shape, SNR and timing offset are to be estimated or are known.

It should be noted that a maximum likelihood classifier is optimal in the Bayesian sense and an estimate of PSK/QAM modulation using this classifier will be the minimum variance unbiased estimate of the PSK/QAM modulation types. This estimator being the minimum variance unbiased estimator is not attained without a cost, however, because the computational complexity associated with correlating all the possible symbols of all the possible sets of symbols to classify the candidate modulation types must be accounted for. Thereby, this ultimately means that in a given receiver, correlators must be implemented for both PSK and QAM modulation schemes, for every variant of both schemes, i.e., BPSK, PSK, 8PSK, QAM4, QAM16. The output of each correlation receiver will be measured against the output of each other candidate and a likelihood decision is made on a symbol-by-symbol basis or can be averaged over a number of symbols. It is intuitive to grasp at this point, how a classifier of this type will yield better and better results as more symbols are taken into consideration before a decision is made on the modulation type. A classifier of this type is said to be asymptotically optimal in that it will achieve the Cramer Rao lower bound [5] for lengthy data records.

3.3 Digital Modulation Classification using Constellation Shape

In this method it is proposed to use the constellation shape of a received modulated waveform as the template for classifying its modulation type [6]. The author states that "if a digitally modulated signal can be uniquely characterized by its constellation, it should be identifiable by the recovered constellation at the receiver." A modulation classifier of this type is inherently feature based as no distribution is assumed, or parameterization done, on the received waveform. A fuzzy c-means algorithm [7] is used in order to create a two-dimensional (2D) array of points to be used as a constellation grid in order to measure the similarities against a known constellation diagram.

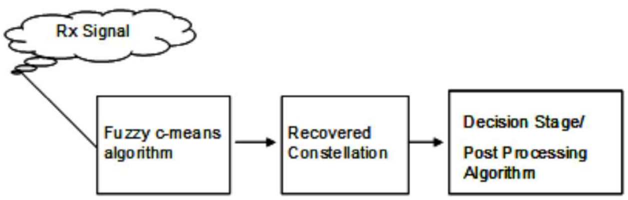

Figure 2. Constellation Feature Based Classification Flow.

The approach seems viable as a feature based modulation classifier, however, in simulations we plan to make some slight changes to the original decision stage in order to possibly implement a 2D correlation based classifier. If this is not done, some additional post processing, such as an image processing algorithm, must be run in order for decisions to be made on the modulation type.

The author does not comment much on the computational complexity of the fuzzy c-means algorithm in order to attain a received constellation grid, but being one of the neural network type algorithms it may not be trivial to implement. Either our 2D correlation based detection or a post image processing algorithm used as a discriminator between the received constellation and the template constellation is known to be memory and computationally intensive.

4 Results

To understand the strengths and weaknesses of the various algorithm type, and thus extend current work in the field, it was attempted to obtain the same results as those obtained in the original works of [2,4,6]. The algorithms and simulations were performed using MATLAB. For the DFT of Phase Histogram method, Figure 3 shows the histogram of the phase for 96 symbols at various signal-to-noise ratios (SNR). It can be seen that as the SNR increases the histogram shows less ambiguity in the classified phase results.

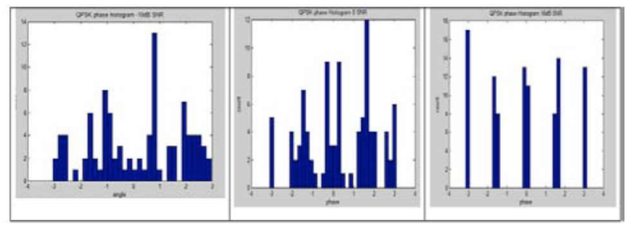

Figure 3. Phase Histogram for QPSK Signal for various SNR.

Figure 4a illustrates the magnitude of the DFT of the phase histogram as the authors propose in their algorithm for a 10dB Eb/No for a QPSK modulation scheme and Figure 4b shows the correct classification being made as the DFT bin with the largest magnitude being four.

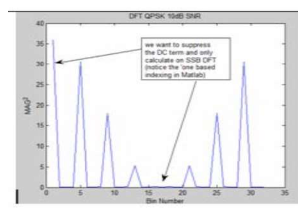

Figure 4a. FFT Magnitude of QPSK Phase Histogram.

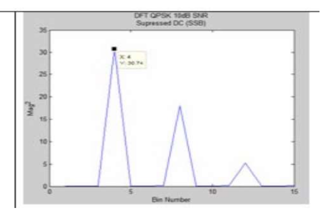

Figure 4b. FFT Magnitude of QPSK Phase Histogram Positive Frequency Suppressed DC.

Lastly, Figure 5a shows the plots of correct classification percentage as a function of SNR for BPSK, QPSK and 8PSK modulation schemes using DFT of Phase Histogram method. The classifier indeed does perform well in low SNR environments.

Although not illustrated in the Figures 3-5b, it is interesting to note that the classifier behaves much like a maximum likelihood classifier, as the performance seems to increase as the length of the data record increases.

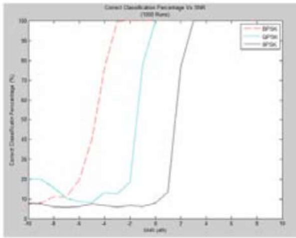

Figure 5a. Correct Classification Percentage DFT of Phase Histogram Method.

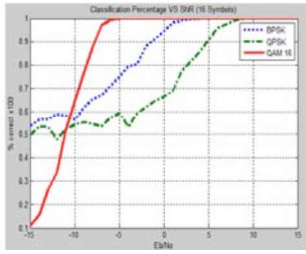

Figure 5b. Correct Classification Percentage of Maximum Likelihood Method.

For the Maximum Likelihood Modulation Classifier for PSK/QAM we simulated three different modulation types and recorded the results of correct classification percentage for 16 symbols after a Monte Carlo analysis for 200 runs. The ML classifier seems to perform very well, as expected. Although unexpected, the QAM16 correct classification percentage is better than both the BPSK and the QPSK (Figure 5b) which is unintuitive. This result may be attributed to the large difference in the energy received for a QAM16 symbol over a BPSK or QPSK symbol thus leading into an interesting point to make about comparisons of autonomous modulation classifiers.

Observing Figures 5a and 5b, one might prematurely jump to a conclusion that the DFT of phase histogram method, though being a feature based classifier outperforms the ML based classifier. This conclusion would be slightly incorrect for two reasons. First, the ML classifier classification percentage was done with less received symbols than the DFT of phase classifier and the ML classifier only claims to be optimal for lengthy data records. Secondly, the feature based classifier assumes no statistical parameterization of the received waveform at all. To compare two different classifiers fairly, we must do so on a statistical basis or measure how close an estimator comes to being the minimum-variance unbiased estimator. The important thing to note is there is no gold standard or set criterion to measure one classifier versus another, thus leading to a more subjective notion if one deems a classifier 'better' than another without being able to assess how close the variance of the estimator comes close to the Cramer Rao lower bound.

Our last simulations show a clean constellation grid – illustrated in Figure 6 – constructed from Gaussian functions that are to be used in a 2D correlation detection for AMC of PSK symbols. The approach is different from the author's proposed scheme but is intended to be robust in the since that we plan to be able to change the template Gaussian functions to match the expected SNR of the received waveform.

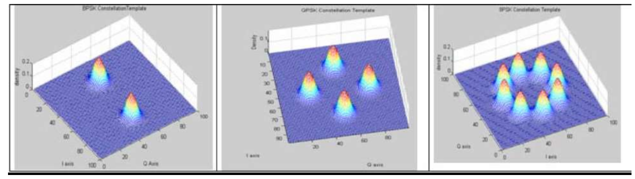

Figure 6. Gaussian Populated Constellation Grid for BPSK QPSK and 8PSK to be used for Feature Based Template.

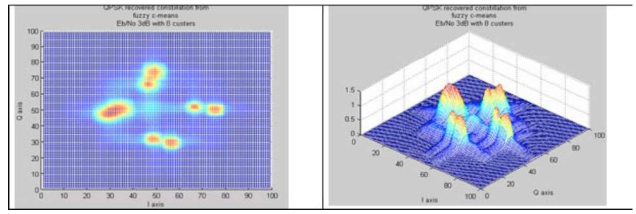

Figure 7. Simulated Fuzzy C-Means Reconstructed Constellation (QPSK 3dB Eb/No).

The final figure (Figure 7) shows the reconstructed grid template using the 'fuzzy c-means' for a QPSK signal with a 3dB Eb/No. Although the final 2D decision stage has not been implemented as of yet, the plan is to quantify a single value resulting from the correlation process as a measure of the modulation type.

5 Conclusions

Although autonomous modulation classification techniques have received much interest over the last decade due to the need to use an allotted frequency spectrum efficiently for digital communications, the field is still in its infancy stage in the sense that there are no defined metrics to adequately and fairly compare one classifier to another. Many feature based classifiers have been proposed in order to escape the heavy computational complexity of an optimal likelihood classifier and render them as 'good enough' for many practical applications. However, a question may be posed as to the ease of modification or extendibility of a feature based classifier. As in the case of software defined radio, some of the main advantages over traditional hardware radio would be its scalability and its ability to be reconfigurable with software updates. Whereas in [2] a feature based algorithm is proposed to extend a PSK automatic classifier to also classifying QAM signals using a DFT of Phase hybrid scheme, future work might focus on the feasibility of using a FB classifier such as that in [4] where many of the constellation points will be shared between a PSK and a QAM modulation scheme.

It seems that a likelihood classifier would be extendable if the approach is to correlate all the possible symbols of all the possible sets of symbols of the candidate modulation types that one may be trying to classify, even though future initiatives must focus on its computational feasibility. Therefore, the road to 'intelligent radio' has yet to be fully paved which leaves much work to be done in this field of study.

Acknowledgments

This work is performed under a contract from NASA for systems engineering and software defined radio research.

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