Automatic Modulation Recognition for Aeronautical Telemetry

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Automatic Modulation Recognition for
Aeronautical Telemetry

Jacob Frogget

A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Science

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ABSTRACT

Automatic Modulation Recognition for Aeronautical Telemetry

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This thesis explores automatic modulation recognition as applied to PCM/FM, SOQPSK-TG and ARTM CPM. It found that the likelihood based approach is intractable. The statistical features of the amplitude, phase and frequency are ineffective at distinguishing these modulation types. A method based on the phase changes between symbols is developed and shows that as long as symbol timing is established, this method can effectively distinguish PCM/FM, SOQPSK-TG and ARTM CPM for signal-to-noise ratios above 30 dB. Another method, the Bianchi-Loubaton-Sirven technique, was able to distinguish PCM/FM and SOQPSK-TG but was unable to distinguish ARTM CPM. A happy byproduct of this classification algorithm is a reasonably accurate estimate of the bit rate. Simulation results show that this classifier works essentially error-free for signal-to-noise ratios above 20 dB and for sufficiently high resolution in the search algorithms required by the maximizations.

Keywords: modulation recognition, aeronautical telemetry
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CHAPTER 1. INTRODUCTION

1.1 Background

Automatic modulation recognition has applications ranging from communication interception for the military to cognitive radio. It can also be used in governmental monitoring and regulation of communication signals [1]. This paper explores the application of these techniques to the modulations used in aeronautical telemetry. Given the scenario where an aircraft or missile is authorized to transmit at a given bit rate using PCM/FM, SOQPSK-TG, or ARTM CPM, a technician could use this tool to verify that the transmitter has been set up correctly and is operating properly.

1.2 CPM Representation of Modulations Used in Aeronautical Telemetry

Both PCM/FM and SOQPSK-TG can be thought of as special cases of continuous phase modulation (CPM). The complex-valued (I/Q) representation for a CPM signal \( s(t) \) is

\[
s(t) = \exp\{j\phi(t)\}
\]  

where the phase, \( \phi(t) \) is a pulse train expressed as

\[
\phi(t) = 2\pi h \sum_k a(k) \gamma(t - kT_s)
\]  

where \( T_s \) is the symbol period (\( 1/T_s \) is the symbol rate); \( h \) is the digital modulation index that quantifies the phase shift for each symbol; and \( \gamma(t) \) is the phase pulse that is usually thought of as the time integral of a frequency pulse \( f(t) \) that spans \( L \) symbols. The convention [2] is to normalize \( f(t) \) to have area \( \frac{1}{2} \) so that \( \gamma(t) = \frac{1}{2} \) for \( t \geq LT_s \). In the CPM literature, modulations with \( L = 1 \) are called full response CPM whereas modulations with \( L > 1 \) are called partial response CPM.
PCM/FM may be expressed as a CPM. The elements of (1.2) are defined as follows. If the bit sequence $b(k) \in \{0, 1\}$ is the $k$-th bit, then the $a(k)$ are related to the bits via the mapping

$$a(k) = \begin{cases} 
-1 & b(k) = 0 \\
+1 & b(k) = 1.
\end{cases} \quad (1.3)$$

The modulation index is $h = 0.7$ and the frequency pulse is

$$f(t) = \begin{cases} 
\frac{1}{4T_b} \left[ 1 - \cos \left( \frac{\pi t}{T_b} \right) \right] & -T_b \leq t \leq T_b \\
0 & \text{otherwise}
\end{cases} \quad (1.4)$$

where $T_b$ is the bit period ($1/T_b$ is the bit rate). Since $a(k)$ and $b(k)$ are produced at the same rate, the “bit rate” and the “symbol rate” are the same. The frequency pulse is plotted in Figure 1.1. Note that $L = 2$ for PCM/FM.

SOQPSK-TG may also be expressed as a partial response CPM. The elements of (1.2) are defined as follows: The relationship between the $k$-th bit $b(k) \in \{0, 1\}$ and the “symbol” $a(k)$ involves a binary-to-ternary mapping. First define

$$u(k) = \begin{cases} 
-1 & b(k) = 0 \\
+1 & b(k) = 1.
\end{cases} \quad (1.5)$$

The $k$-th “symbol” $a(k)$ is given by

$$a(k) = (-1)^{k+1} \frac{u(k-1)[u(k) - u(k-2)]}{2}. \quad (1.6)$$

This produces a constrained ternary output $a(k) \in \{-1, 0, +1\}$. Note that each new $b(k)$ produces a new $a(k)$. Consequently, the $a(k)$ and $b(k)$ are produced at the same rate so that the “symbol rate” and the “bit rate” are the same. The modulation index is $h = 1/2$. The frequency pulse is a
spectral raised cosine windowed by a temporal raised cosine:

\[
f(t) = C \frac{\cos \left( \frac{\pi \rho B t}{2 T_b} \right)}{1 - 4 \left( \frac{\rho B t}{2 T_b} \right)^2} \times \frac{\sin \left( \frac{\pi B t}{2 T_b} \right)}{\pi B t} \times w(t),
\]

(1.7)

\[
w(t) = \begin{cases} 
1 & 0 \leq \left| \frac{t}{2 T_b} \right| < T_1 \\
\frac{1}{2} \left[ 1 + \cos \left( \frac{\pi}{T_2} \left( \frac{t}{2 T_b} - T_1 \right) \right) \right] & T_1 \leq \left| \frac{t}{2 T_b} \right| \leq T_1 + T_2 \\
0 & \text{otherwise}
\end{cases}
\]

(1.8)

where \( C \) is a constant to make the area of \( f(t) \) one-half. The constants \( \rho \) and \( B \) represent the rolloff factor and an additional time scaling factor, respectively, while the constants \( T_1 \) and \( T_2 \) indicate the width of the passband and transition band of the windowing filter. These four constants are given in the IRIG-106 standard [3] as

\[
\rho = 0.7, B = 1.25, T_1 = 1.5, T_2 = 0.5.
\]

(1.9)

This produces a partial response pulse shape with \( L = 8 \). This frequency pulse is also plotted in Figure 1.1.

ARTM CPM may also be expressed as a CPM. The elements of (1.2) may be expressed as follows. In this case, two bits are mapped to a single symbol so the “bit rate” is twice the “symbol rate.” If \((b_0(k), b_1(k)) \in \{00, 01, 10, 11\}\) be the \(k\)-th pair of bits, then \( a(k) \) is given via the mapping

\[
a(k) = \begin{cases} 
-3 & (b_0(k), b_1(k)) = 00 \\
-1 & (b_0(k), b_1(k)) = 01 \\
+1 & (b_0(k), b_1(k)) = 10 \\
+3 & (b_0(k), b_1(k)) = 11.
\end{cases}
\]

(1.10)
The frequency pulse is

\[ f(t) = \begin{cases} \frac{1}{2LT_s} \left[ 1 - \cos \left( \frac{2\pi t}{LT_s} \right) \right] & 0 \leq t \leq LT_s \\ 0 & \text{otherwise} \end{cases} \]  

(1.11)

where \( L = 3 \). The frequency pulse is plotted in Figure 1.1. The modulation indexes are \( h_0 = \frac{4}{16} \) and \( h_1 = \frac{5}{16} \) which alternate every symbol. Thus, ARTM/CPM is a “multi-index” or “multi-h” CPM.

1.3 Outline of Thesis

This thesis will explore several methods used in modulation recognition. Many of these methods are used for a variety of modulation types but focus is given on whether they are effective for PCM/FM, SOQPSK-TG, and ARTM CPM as described in this chapter. Descriptions of the methods are given as well as simulation results to demonstrate their effectiveness. The Bianchi method is found to be effective for PCM/FM and SOQPSK-TG and is described in more detail.
The phase change method is then found to be effective if the symbol rate is known and samples are taken at the end of each symbol period. The accuracy of these estimators is presented. Several variations on the described recognition methods are also presented along with their simulation results. Some comments on possible future work are then given.
CHAPTER 2. SURVEY OF MODULATION RECOGNITION TECHNIQUES

A variety of methods for modulation recognition have been described in the open literature. Overviews can be found in [1, 4]. Generally, these methods take either a likelihood approach, or a feature based approach. A problem closely related to classifiers is blind estimation of the symbol rate for a digitally modulated carrier. Of particular interest are blind symbol rate estimators for CPM signals.

2.1 Signal Model

For automatic recognition, the receiver observes

\[ y(t) = s(t - \tau)e^{j2\pi f_0 t} + n(t) \]  \hspace{1cm} (2.1)

and processes the observation \( y(t) \) to determine if \( s(t) \) corresponds to PCM/FM, SOQPSK-TG or ARTM CPM. In (2.1), \( \tau \) is an unknown delay, \( \Delta f_0 \) is the uncompensated frequency offset in Hz, and \( n(t) \) models the additive thermal noise and is a complex-valued Gaussian random process with zero mean and autocovariance function

\[ \frac{1}{2} \mathbb{E} \{ n(t)n^*(t - \tau) \} = N_0 \delta(\tau) \]  \hspace{1cm} (2.2)

where \( \delta(\tau) \) is the Dirac delta function.

2.2 Likelihood Based Approaches

A likelihood based approach forms a likelihood function of the signal. It then chooses the modulation type which maximizes this function. This approach was taken in [5] which was effective at distinguishing QAM with different constellations. Functions for PSK, FSK and QAM
are described in [1, 4]. Likelihood based approaches generally are effective at distinguishing between different constellations of the same modulation type, but are not effective in distinguishing between different types of modulation or modulations that differ by too many parameters [1].

The log-likelihood function for this case is derived as follows: the signal model shows that

\[ y(t) = s(t - \tau)e^{j2\pi f_0 t} + n(t) = \exp \left\{ j2\pi h \sum_k a(k) \gamma(t - kT_s - \tau) \right\} e^{j2\pi f_0 t} + n(t). \]  

(2.3)

Sampling \( y(t) \) gives

\[ y(i) = \exp \left\{ j2\pi h \sum_k a(k) \gamma(iT - kT_s - \tau) \right\} e^{j2\pi f_0 T_i} + n(iT) \]  

(2.4)

where \( y(i) \) is the \( i \)-th sample of \( y(t) \). Let \( y = [y(0), y(1), ..., y(N - 1)]^T \) and \( a = [a(0), a(1), ..., a(M - 1)] \) correspond to the sequence of samples of \( y(t) \) and the sequence of symbols transmitted respectively. This allows us to make the log-likelihood function

\[ f(y|h, \gamma, a, \tau, T_s, \Delta) = \frac{1}{2\pi N_0} \exp \left\{ -\frac{1}{N_0} (y - X)^H (y - X) \right\} \]  

(2.5)

where

\[ X = X_0, X_1, ..., X_{N-1} \]  

(2.6)

and where

\[ X_i = \exp \left\{ j2\pi h \sum_k a(k) \gamma(iT - kT_s - \tau) \right\} \exp^{j2\pi f_0 T_i}. \]  

(2.7)

The conditional probability

\[ f(y|h, \gamma) = \int \cdots \int f(y|h, \gamma, a, \tau, T_s, \Delta)f(a, \tau, T_s, \Delta)d\alpha d\tau dT_s d\Delta \]  

(2.8)

is needed for the log-likelihood function,

\[ \Lambda(h, \gamma) = \ln f(y|h, \gamma). \]  

(2.9)
A decision can then be made by

$$\text{modulation} = \arg \max_{h, \gamma} \{ \Lambda(h, \gamma) \}.$$ (2.10)

The values for $h$ and $\gamma$ are known for each modulation. Therefore, the value of $\Lambda$ for a given modulation would be determined by using its corresponding values of $h$ and $\gamma$. The number of integrals in (2.8) is $M + 3$. This makes the function very difficult to evaluate. Also, since $T_s$ is unknown, for a given number of samples, even the number of elements in $\mathbf{a}$ is unknown. These factors render the problem intractable. In general, likelihood functions work best when applied to recognizing different constellations of the same modulation type [1, 4]. This shows the advantage of finding features of the signal to distinguish between these modulation types instead of the likelihood function.

### 2.3 Some Feature Based Approaches to Modulation Recognition

Most methods take a feature based approach to modulation recognition, which means they extract certain features from a signal and then make a decision based on these features. Some decision making methods could include comparing values to a threshold, euclidean distance, or even machine learning methods such as artificial neural networks or support vector machines [1, 6, 7]. When a classifier is designed to distinguish between many types of modulations, a binary tree decision structure can be developed to sort the modulations into different groups, making one decision at a time [1, 4, 7–11]. Each feature is used to narrow down the types until only one remains. The machine learning decisions take all the features from the signal at once and make a decision based on parameters collected from training sequences [6, 7].

Most features of a signal are taken from its instantaneous amplitude, phase, or frequency. Some methods also look at the RF characteristics of a signal to distinguish modulation types [6, 7, 11]. Some of these features are described here and the applications of these features are shown in the following sections. The variance of the amplitude, phase, or instantaneous frequency can determine if there is information contained in that feature. Let $x$ represent one of the quantities for amplitude, phase, or instantaneous frequency. The variance is given by

$$\sigma^2 = E[(x(t) - \mu)^2]$$ (2.11)
where $\mu = E[x(t)]$, and $E[\cdot]$ is the expectation operator. Kadambe et al. [6] use skewness to distinguish signals that are non symmetric as one of the features of its machine learning system. Skewness is defined as

$$s = \frac{E[(x(t) - \mu)^3]}{\sigma^3} \tag{2.12}$$

where $\mu$ and $\sigma$ were defined previously. The kurtosis coefficient is used in several cases to distinguish signals with certain distributions. The kurtosis coefficient is defined as

$$K = \frac{E[x^4(t)]}{(E[x^2(t)])^2} \tag{2.13}$$

The kurtosis coefficient measures the “peakedness” of a distribution about a given point. The kurtosis of the instantaneous frequency can be used to distinguish FM signals from FSK signals [10, 11] and the kurtosis of the instantaneous amplitude is effective in distinguishing MPSK from QAM signals [4, 9].

### 2.3.1 Amplitude Features

AM, ASK, or QAM signals can be distinguished from other types by examining the amplitude of the signal of interest over time [8–11]. If the amplitude varies, then there is information contained in the amplitude of the signal, otherwise, information is contained in either the phase or frequency of the signal. Since all CPM signals have constant amplitude so any method looking at the amplitude of the signal will not help to distinguish the modulations described in this thesis.

### 2.3.2 Phase Characteristics

Analyzing the variance of the unwrapped phase of the signal can help to distinguish signals that contain information in their phase from those that have constant phase [1, 4, 10, 11]. Since all the modulations in this thesis contain information in the phase, this could be a distinguishing factor, but it will be more difficult than simply determining if the information is there or not. Some trial runs of the variance of the unwrapped phase for each modulation type can be shown in Figure 2.1. This figure shows that the variance of the phase is not helpful to this problem. Section 2.5 describes
Figure 2.1: Several trials of the sample variance of the unwrapped phase of PCM/FM, SOQPSK-TG and ARTM CPM. Each trial was calculated from 1000 randomly generated symbols at 35 samples/symbol.

another method for analyzing the phase changes between symbols as a method to classify these modulations.

Figure 2.2 shows the sample skewness for randomly generated signals of PCM/FM, SOQPSK-TG, and ARTM CPM. The plot shows that skewness can not distinguish modulations of these types. All trials give points which are small numbers which are centered around zero. These results are to be expected because the density function of the phase is symmetric.

Figure 2.3 shows several trials where the magnitude of the sample kurtosis coefficient of the complex signal is found for each modulation type in zero noise. The plot shows that this is not an effective method to classify these modulation types.
2.3.3 Instantaneous Frequency

The instantaneous frequency of a signal can sometimes be leveraged in signal classification. This section describes how the instantaneous frequency of a signal is obtained and some methods for analyzing it.

The instantaneous frequency is the time-derivative of the phase of a signal [12]. Given the signal $y(t) = I(t) + jQ(t)$, the phase can be found by

$$\phi(t) = \arctan \frac{Q(t)}{I(t)}.$$  \hspace{1cm} (2.14)

So the instantaneous frequency is then

$$\text{instantaneous frequency} = \frac{d}{dt} \phi(t) = \frac{\dot{Q}(t)I(t) - I(t)\dot{Q}(t)}{I^2(t) + Q^2(t)}$$ \hspace{1cm} (2.15)

where $\dot{I}$ and $\dot{Q}$ are the time-derivative of $I(t)$ and $Q(t)$ respectively.
For some modulation types, the same methods used previously in modulation recognition can be applied to the instantaneous frequency instead. For example, statistics are used on the amplitude of a signal to distinguish it from others [10]. These same statistics could be applied to the instantaneous frequency of a signal instead of the amplitude in order to classify other types of modulation.

Figure 2.4 shows plots of the instantaneous frequency over time for each modulation type. By comparing the three plots even visually, differences between the three are apparent, especially distinguishing PCM/FM from the other two. This gives the impression that the instantaneous frequency could be used to classify the modulation types.

The variance of the instantaneous frequency is somewhat effective, particularly in distinguishing PCM/FM from the other two, however it has its limitations. Figure 2.5 shows the sample variance of the instantaneous frequency for PCM/FM, SOQPSK-TG and ARTM CPM as a function of $E_b/N_0$. The sample variance was determined by using long segments of simulated data at
Figure 2.4: Plot of instantaneous frequency over time (samples) for PCM/FM (top), SOQPSK-TG (middle), and ARTM CPM (bottom). The data was generated at 35 samples/symbol.

20 samples/symbol. The values are very consistent between tests, however, picking a threshold for classification is very difficult as the variance changes with the noise power. It also suffers from the same problem as the kurtosis coefficient in that the values change depending on the number of samples/symbol. If a specific $E_b/N_0$ and symbol rate could be guaranteed, then this method would be very effective, however in a real-life implementation, this is impractical.

Figure 2.6 shows the sample skewness of the instantaneous frequency for each modulation type for a series of simulations without noise. The figure shows that no clear threshold could be chosen to classify them so the modulations used in this thesis are not distinguishable by skewness.
Figure 2.5: Plot of the variance of instantaneous frequency for different values of $E_b/N_0$ for PCM/FM, SOQPSK-TG, and ARTM CPM. The data was generated by taking the sample mean value of 1000 trials of finding the variance of 5000 symbols at 15 samples/symbol for each $E_b/N_0$. The plot shows all the points are small numbers around zero. This is to be expected because the density function of the instantaneous frequency is symmetric.

Figure 2.7 shows the sample average of the sample kurtosis coefficient of the instantaneous frequency. This is shown over a range of $E_b/N_0$ for PCM/FM, SOQPSK-TG, and ARTM CPM. The sample kurtosis coefficient was found by generating long sets of simulated data created with 20 samples/symbol. The plot shows that at high $E_b/N_0$, the kurtosis of the instantaneous frequency could be used to distinguish PCM/FM from SOQPSK-TG and ARTM CPM. The kurtosis of the instantaneous frequency of SOQPSK-TG and ARTM CPM are too close to each other to be a distinguishing factor. The kurtosis value is also dependent on the number of samples per symbol, even at high $E_b/N_0$. Unless this value is provided to the detector, it will be completely ineffective for recognizing these modulation types.

Another method to obtain the instantaneous frequency is by using the zero-crossing technique. This technique creates a sequence that measures the distance between when the signal
Figure 2.6: Results of a series of simulations computing skewness of the instantaneous frequency for PCM/FM, SOQPSK-TG, and ARTM CPM. Each trial was calculated from 1000 randomly generated symbols at 35 samples/symbol.

crosses zero, essentially making a sequence of the instantaneous signal period. Grimaldi et al. [8] uses the zero crossing sequence to distinguish FSK signals from PSK signals. The signal period for FSK signals is constant inside each symbol but varies between symbols, where the signal period for a PSK signal presents peaks corresponding to each phase change.

The zero crossings of the instantaneous frequency for each modulation type were tested to see if any patterns arose. The results of a trial run with no noise can be seen in Figure 2.8. The figure shows that no clear pattern can be seen, even without noise. The only noticeable feature is that the plot for PCM/FM has lower values than the other two. However, after running several trials, it was clear that these values vary too much to be used reliably.

Most of the modulation classification methods described so far rely on statistics to analyze the distributions of the signal. None of these methods have been very useful because the modulations in this thesis are too similar to be distinguished by statistical distributions. The next sections describe some other types of methods for signal classification.
Figure 2.7: Plot of the kurtosis of the instantaneous frequency for different values of $E_b/N_0$ for PCM/FM, SOQPSK-TG, and ARTM CPM. The data was generated by taking the sample mean value of 1000 trials of finding the kurtosis of 5000 symbols at 15 samples/symbol for each $E_b/N_0$.

2.4 The Bianchi Modulation Recognition Technique

The Bianchi-Loubaton-Sirven technique [13–15] is very effective at determining the bit rate $R_b$ and modulation index $h$ of a CPM signal. This technique is based on the following line of reasoning. Let $s(t)$ be a CPM signal with modulation index $h$:

$$s(t) = e^{j2\pi h \sum_k a(k) \gamma(t-kT_s)}$$  \hspace{1cm} (2.16)

and let $g$ be a positive real number. Now form $s^g(t)$. This may be expressed as

$$s^g(t) = \left( e^{j2\pi h \sum_k a(k) \gamma(t-kT_s)} \right)^g = e^{j2\pi hg \sum_k a(k) \gamma(t-kT_s)}.$$  \hspace{1cm} (2.17)

This shows that $s^g(t)$ is a new CPM signal with modulation index $hg$. The recognition algorithm is based on the following observations:
Figure 2.8: Result of the zero crossings of the instantaneous frequency for PCM/FM (top), SOQPSK-TG (middle), and ARTM CPM (bottom). Each trial was calculated from 1000 randomly generated symbols at 35 samples/symbol.

- if $hg \neq \text{integer}$, then $E\{s^g(t)\} = 0$.

- if $hg = \text{even integer}$, then $E\{s^g(t)\}$ is periodic with period $T_s$.

- if $hg = \text{odd integer}$, then $E\{s^g(t)\}$ is periodic with period $2T_s$, but only the odd harmonics are present.

These observations are neatly captured in the function

$$r(g, \alpha) = \lim_{T \to +\infty} \frac{1}{T} \int_0^T E\{s^g(t)e^{-j2\pi\alpha t}\} \, dt$$  \hfill (2.18)
where $E\{ \cdot \}$ is the statistical expectation operator. Here, $\alpha$ is the frequency variable. Based on the observations regarding $hg$, $r(g, \alpha)$ is non-zero if and only if $hg$ is an integer. The periodicity of $E\{ s^g(t) \}$ will show up as spectral lines on the $\alpha$-axis. If $hg$ is an even integer, then these spectral lines will appear in $r(g, \alpha)$ when $\alpha$ is an integer multiple of $1/T_s$. Similarly, when $hg$ is an odd integer, then the periodicity of $E\{ s^g(t) \}$ will produce spectral lines in $r(g, \alpha)$ when $\alpha$ is an odd-integer multiple of $1/2T_s$.

Now, as stated above, the recognition algorithm operates on $y(t)$ rather than $s(t)$. Thus, the function $r(g, \alpha)$ is defined in terms of $y(t)$ instead of $s(t)$:

$$r(g, \alpha) = \lim_{T \to +\infty} \frac{1}{T} \int_0^T E\{ y^g(t) e^{-j2\pi\alpha t} \} dt.$$  \hspace{1cm} (2.19)

In a practical implementation, the automatic recognition algorithm operates on a sampled version of $y(t)$. Let $y(k)$ be the $k$-th sample of $y(t)$ and suppose $N$ samples are available for processing. In this case, the function (2.19) is replaced by [13]

$$r_N(g, \alpha) = \frac{1}{N} \sum_{k=0}^{N-1} \left\{ \frac{y(k)}{|y(k)|} \right\}^g e^{-j2\pi\alpha k}.$$  \hspace{1cm} (2.20)

In the noiseless case, $y(k) = y(k)/|y(k)|$. This normalization helps to regulate influence from noise. The function $r_N(g, \alpha)$ is maximized when $g$ is an integer multiple of the modulation index and $\alpha$ is a multiple of the normalized symbol rate (ratio of symbol rate to sample rate) as described above. Note that in addition to estimating the modulation index, this algorithm also estimates the bit rate. This algorithm was found to work well for PCM/FM and SOQPSK-TG. The results are found in Chapter 3.

### 2.5 Using Phase Changes Between Symbols to Identify a CPM Signal

CPM signals hold all of their information in the phase of the signal [16] as defined in (1.1) and (1.2). The parameters that define the phase are unique for each of the CPM signals used in this paper. Therefore, the phase changes between symbols are also unique, and can be used for classification of these signals. The change in phase from one symbol to the next represents the transmission of a single symbol. Because all the CPM signals in this paper are partial response,
the symbols on either side of a given symbol will also influence the change in phase. When a string of symbols is transmitted for a partial response CPM, there are many possible phase changes that could take place, depending on the symbols sent. The three factors that define the phase changes are the modulation index \( h \), the phase pulse shape \( g \), and the symbols \( a \) as shown in (1.2). Analysis of these phase changes could give information about the modulation type if they can be captured properly. This method was found to partially work for the aeronautical telemetry modulations and the results are presented in Chapter 4.

2.6 Music Recognition

Song recognition programs have become very popular on a variety of mobile devices. They are able to listen to a short segment of a song on the radio and tell the user what the song is. The programs work very quickly and are able to identify a song among millions with only a few seconds of sample data in ambient noise [17].

The algorithm works by creating a “fingerprint” of each song included in a database. Every sample audio file is “fingerprinted” in the same way to compare with the database. These “fingerprints” are made by creating a spectogram, or plot of frequency and intensity over time, of the audio file. The peak points in the spectogram are used for identification. The algorithm is careful to select the locally peak points so that any 10 second segment can be used for identification. The locations of the peak points are made into constellations and made into hashes for fast querying of the database. This makes it possible to only send a small amount of data over an internet link to find the song in the database. This method is very accurate even at low signal-to-noise ratios and short sample lengths [17].

Unfortunately, this method does not work well for the application in this thesis. The method relies on the fact that it has a database of exact signal fingerprints, which is unavailable in this case because the data symbols are unknown. The music recognition algorithm does not even claim to work for live performances, because the fingerprint would be different enough to throw off the algorithm. It does, however, claim to still work for slight variations in music tempo. Sometimes radio DJ’s will speed up songs to fit them in before a commercial break, and these songs can still be recognized. This could translate to being effective for CPM recognition even when the symbol
rate is not known exactly. However, the data symbols would still all need to be known for any part of this method to work.
CHAPTER 3. BIANCHI MODULATION RECOGNITION ALGORITHM FOR AERONAUTICAL TELEMETRY

After experimenting with several different automatic recognition techniques, we discovered that the Bianchi-Loubaton-Sirven technique \cite{13, 18} described in Section 2.4 produced the most reliable results to distinguish between PCM/FM and SOQPSK-TG. Unfortunately, this method was ineffective at distinguishing ARTM CPM from the other two. The reasons for this are described later in section 3.2.

The first step in applying the Bianchi technique to the aeronautical telemetry problem is to evaluate $r_N(g, \alpha)$ at values of $g$ that are integer multiples of reciprocals of the two modulation indexes ($h = 0.7$ for PCM/FM and $h = 0.5$ for SOQPSK-TG). The question is, do we use an even multiple of the reciprocal modulation indexes or an odd multiple? In the first case, $r_N(g, \alpha)$ will display a periodic component at the bit rate. In the second case, $r_N(g, \alpha)$ will display a periodic component at odd multiples of half the bit rate. In the original work, Bianchi \cite{13} preferred the second case (that is, $g = 1/h$). This worked best for full response CPM. Indeed, Bianchi pointed out that his approach was best suited for full response CPM and speculated that it would not work well for partial response CPM. Our results show that the Bianchi approach does work for PCM/FM and SOQPSK-TG (both partial response CPM) when $g = 2/h$.

The algorithm is outlined as follows. Let $y(k)$ for $k = 0, 1, \ldots, N - 1$ be the $N$ samples of the received waveform and let $g_0 = 2/0.7$ (this is for PCM/FM) and let $g_1 = 2/0.5 = 4$ (this is for SOQPSK-TG). Now find

$$R_0 = \max_{\alpha} \left\{|r_N(g_0, \alpha)|^2\right\}, \quad \hat{\alpha}_0 = \arg \max_{\alpha} \left\{|r_N(g_0, \alpha)|^2\right\},$$

$$R_1 = \max_{\alpha} \left\{|r_N(g_1, \alpha)|^2\right\}, \quad \hat{\alpha}_1 = \arg \max_{\alpha} \left\{|r_N(g_1, \alpha)|^2\right\}.$$
Finally, the decision is:

\[
\text{modulation} = \begin{cases} 
\text{PCM/FM with bit rate } \hat{\alpha}_0 \times \text{sample rate } & R_0 \geq R_1 \\
\text{SOQPSK-TG with bit rate } \hat{\alpha}_1 \times \text{sample rate } & R_0 < R_1.
\end{cases}
\] (3.3)

A simple illustration of the concept is given in Figure 3.1. In Figure 3.1 (a), the input samples \(y(n)\) are samples of PCM/FM with an equivalent sample rate of 20 samples/bit. Here, both \(|r_N(g_0, \alpha)|^2\) and \(|r_N(g_1, \alpha)|^2\) are plotted as a function of \(\alpha\). We observe a peak in \(|r_N(g_0, \alpha)|^2\) at \(\alpha = 0.05\) bits/sample corresponding to the normalized bit rate of \(1/20 = 0.05\) bits/sample. There are peaks in \(|r_N(g_1, \alpha)|^2\) as well, but none of these peaks are as high as the peak in \(|r_N(g_0, \alpha)|^2\). In Figure 3.1 (b), the \(y(n)\) are samples of SOQPSK-TG with an equivalent sample rate of 20 samples/bit. There is a peak in \(|r_N(g_1, \alpha)|^2\) at \(\alpha = 1/20\) as expected and this peak is higher than any peak in \(|r_N(g_0, \alpha)|^2\). The most noticeable feature here is the very strong peak at \(|r_N(g_1, 0)|^2\). The negative consequence of this is that (3.2) will always give \(\hat{\alpha}_1 = 0\) and \(R_1 > R_0\) when the true signal is SOQPSK-TG. While the decision may be correct, the bit rate estimate is very bad. To fix this problem, the searches (3.1) and (3.2) omit the region around \(\alpha = 0\).

### 3.1 Simulation Results

The performance of the algorithm (3.1) – (3.3) was simulated using samples of PCM/FM and SOQPSK-TG both at an equivalent sample rate of 20 samples/bit. The maximizations (3.1) and (3.2) were carried out using the FFT algorithm to provide a coarse estimate, followed by parabolic interpolation [19] to generate a fine estimate. The interpolated maxima were used for \(R_0\) and \(R_1\). The performance of both the classifier and the bit rate estimator, as a function of signal-to-noise ratio, was simulated.

The first set of plots, given in Figure 3.2, summarizes the performance of the classifier as a function of signal-to-noise ratio. In the top plot, the \(y(n)\) are samples of PCM/FM and is an estimate of the probability of making the correct decision when the true answer is PCM/FM. The bottom plot of Figure 3.2 is the same except the \(y(n)\) are samples of SOQPSK-TG. Thus, the bottom plot is an estimate of the probability of making the correct decision when the true answer is SOQPSK-TG.
Figure 3.1: Plots of $|r_N(g, \alpha)|^2$ and $|r_N(g_1, \alpha)|^2$ as a function of $\alpha$ for $N = 8192$ at an equivalent sample rate of 20 samples/bit: (a) $|r_N(g_0, \alpha)|^2$ and $r_N|(g_1, \alpha)|^2$ as a function of $\alpha$ when $y(n)$ are samples of PCM/FM; (b) $|r_N(g_0, \alpha)|^2$ and $r_N|(g_1, \alpha)|^2$ as a function of $\alpha$ when $y(n)$ are samples of SOQPSK-TG.
The behavior of the classifier when PCM/FM is the true signal is what one might expect. The performance improves as the signal-to-noise ratio increases and as the observation length increases. (The observation length was set to a power of 2 to leverage the computational advantages of the FFT algorithm.) For the simulation parameters used here, the classifier is making essentially error-free decisions when the signal-to-noise ratio is about 15 dB or higher.

The behavior of the classifier when SOQPSK-TG is true signal are somewhat unexpected. At a low signal-to-noise ratio, the classifier makes the correct decision about 50% of the time. In other words, the decision is completely random. As signal-to-noise ratio increases, one expects the situation to improve, but it does not. The probability that the decision is correct decreases to near zero before increasing. Close examination of Figure 3.1 (b) provides possible explanations.

- Because so much of the energy in $|r_N(g_1, \alpha)|^2$ is concentrated at $\alpha = 0$ and because the region immediately around $\alpha = 0$ is omitted from the search, it does not take much noise power to produce a peak in $|r_N(g_0, \alpha)|^2$ that is higher than any peak in $|r_N(g_1, \alpha)|^2$ for $\alpha \neq 0$. This is why the situation improves as signal-to-noise ratio increases above approximately 17 dB.

- The true peak in $|r_N(g_1, \alpha)|^2$ when SOQPSK-TG is true is much narrower than the peak in $|r_N(g_0, \alpha)|^2$ when PCM/FM is true. Consequently, if the coarse search does not have sufficient resolution, the coarse search may entirely miss the true peak. As we implemented it, the resolution of the coarse search increases (improves) as the observation length increases. We believe this is why the performance dramatically improves when the observation length is doubled from 8192 to 16384 samples.

In summary, the classifier (and estimator as described below) requires both sufficiently high signal-to-noise ratio and search resolution to produce usable results.

The second set of plots, shown in Figure 3.3 summarize the quality of the bit rate estimate used by the classifier. The PCM/FM results are summarized in the top plot of Figure 3.3. The bit rate estimate error variance decreases as signal-to-noise ratio increases, with a sharp transition in the 12–17 dB range for the simulation parameters used. Above the transition range, the error variance exhibits an error floor. This error variance floor is characteristic of two-step (coarse/fine) estimators based on the DFT [19]. The quality of the bit rate estimate also improves as the length
Figure 3.2: Percentage of correct decisions between PCM/FM and SOQPSK-TG when the transmitted signal is PCM/FM (top) and when the transmitted signal is SOQPSK-TG (bottom).

of the observation interval improves: the estimator error variance starts to improve at a lower signal-to-noise ratio and the error variance floor is slightly lower.

The SOQPSK-TG results are summarized in bottom plot of Figure 3.3. As before, the quality of the estimator improves with increasing signal-to-noise ratio, and experiences a floor. But here, the influence of coarse search resolution is dramatic. We believe this is due to the ability of the coarse search to correctly identify the true (very narrow) peak in $|r_N(g_1, \alpha)|^2$ when SOQPSK-TG is true. When the true peak can be properly identified, the estimator error variance is very low. This means a very high quality estimate is available.
Figure 3.3: Bit rate estimate variance when the transmitted signal is PCM/FM (top) and when the transmitted signal is SOQPSK-TG (bottom).

3.2 ARTM CPM and the Bianchi Algorithm

The Bianchi algorithm was ineffective at distinguishing ARTM CPM from either PCM/FM or SOQPSK-TG. It was also unable to determine the symbol rate of any test signal. This is because the Bianchi algorithm requires a specific value of $g$ in order to raise it to this value. The alternating pattern of $h_0 = 4/16$ and $h_1 = 5/16$ does not leave an obvious value of $g = 2/h$ as was the case for PCM/FM and SOQPSK-TG. The values for $h_0$ and $h_1$ are not very far apart, but over long sums, the values are blurred enough so a peak is difficult to find. Another short-coming of ARTM CPM in this case, is the fact that it is more partial response than the other two modulation types.
The assumptions made by Bianchi in developing this method is that the modulation should be full-response so this is also a problem.

### 3.3 Variations on the Bianchi Recognition Algorithm

There are several variations on the algorithm that are worth looking into. These changes were an attempt to find ways to improve either the reliability of the classification or decrease the complexity of the algorithm.

#### 3.3.1 Interpolation

In the original Bianchi algorithm, (see Section 3.1), the true maxima of $|r_N(g_0, \alpha)|^2$ and $|r_N(g_1, \alpha)|^2$ were found using interpolation of the FFT before a decision was made about the modulation type. In this test, the maxima from the course estimates produced from the FFT algorithm were used to find the maximum values without interpolation. Then a decision was made on the modulation type. The estimate of $\alpha$ was then made using the true maximum value by interpolating the FFT. The results of this method can be found in Figure 3.4 and Figure 3.5 which are very similar to the original simulation results.

#### 3.3.2 Absolute Value

As seen in (3.1) and (3.2), the magnitude squared operator is used instead of simply the magnitude. In hardware, this reduces complexity of the computation because a square root function is not needed. To be thorough, the algorithm was tested using $|r_N(g_0, \alpha)|$ and $|r_N(g_1, \alpha)|$ instead, to see if there was any difference in performance. The results of this simulation can be found in Figure 3.6 and Figure 3.7 and show no difference in performance.
Figure 3.4: Percentage of correct decisions between PCM/FM and SOQPSK-TG when the transmitted signal is PCM/FM (top) and when the transmitted signal is SOQPSK-TG (bottom) when interpolating the FFT after a decision is made.

### 3.3.3 No Normalization

Bianchi remarks in his paper that the development of the symbol rate estimator suggests that (2.20) should look more like

$$r_N(g, \alpha) = \frac{1}{N} \sum_{k=0}^{N-1} |y(k)|^g e^{-j2\pi\alpha k}. \quad (3.4)$$

He simply mentions that the use of (2.20) generated better experimental results. The reason for this is that the normalization of $y(k)$ ensures that each element of the sum is taken with equal
weight. In the noiseless case, this makes no difference. However, noise can change the magnitude of each element of \( y(k) \) and disrupt the algorithm considerably. To demonstrate this, a simulation was run using (3.4) in place of (2.20). The results of this simulation can be seen in Figure 3.8 and Figure 3.9.

### 3.3.4 Single FFT Point

As noted in Section 3 and seen in Figure 3.1, there is a strong peak at \( |r_N(g_1, 0)|^2 \). In the algorithm described in Section 2.4, the region around \( \alpha = 0 \) is omitted. This section describes...
Figure 3.6: Percentage of correct decisions between PCM/FM and SOQPSK-TG when the transmitted signal is PCM/FM (top) and when the transmitted signal is SOQPSK-TG (bottom) when using the absolute value instead of magnitude squared.

an attempt to leverage this single point in identifying the modulation type. When \( \alpha = 0 \), (2.20) becomes

\[
N g \frac{1}{N} \sum_{k=0}^{N-1} \left[ \frac{y(k)}{|y(k)|} \right]^g.
\]

A decision is made by taking the ratio of \( r_N(g_0, 0) \) to \( r_N(g_1, 0) \) and comparing it to a threshold. Figure 3.10 and Figure 3.11 show the results when the threshold is 2. Thus, a decision is made
Figure 3.7: Bit rate estimate variance when the transmitted signal is PCM/FM (top) and when the transmitted signal is SOQPSK-TG (bottom) when using the absolute value instead of magnitude squared.

by

\[
\text{modulation} = \begin{cases} 
\text{PCM/FM} & \frac{r_N(g_0,0)}{r_N(g_1,0)} \geq 2 \\
\text{SOQPSK-TG} & \text{otherwise.}
\end{cases}
\] (3.6)

The bit rate is computed as before after a decision is made by computing \(|r_N(g, \alpha)|\) for \(g\) corresponding to the modulation type decided. By looking at the figures, it can be seen that the algorithm favors SOQPSK-TG when the noise is too high. For a data length of at least 16384, a
good decision can be made above about 20dB $E_b/N_0$. The threshold can be adjusted to move this threshold to the left, however, the accuracy at high $E_b/N_0$ decreases.

### 3.3.5 Conclusions on the Variations

Based on Figures 3.4-3.11, the following conclusions can be made.
Figure 3.9: Bit rate estimate variance when the transmitted signal is PCM/FM (top) and when the transmitted signal is SOQPSK-TG (bottom) when not using the normalized signal.

- There is no difference in making a decision between whether the modulation type is PCM/FM or SOQPSK-TG using the values directly computed by the FFT or using the peak value interpolated from the FFT.

- Using the magnitude squared value in (3.1) and (3.2) instead of simply the magnitude has no impact on the identification nor the estimate of $\alpha$. It does make a difference in required resources in a hardware implementation so the preferred method would be magnitude squared.

- Normalizing the noisy received signal is very important to making an accurate decision between PCM/FM and SOQPSK-TG as well as an accurate estimate of $\alpha$. 

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• Using only the first point of the FFT in (2.20) does not produce a very accurate decision. There is too much variance in that first point, even in low noise situations.

3.4 Hardware Test

To really test the effectiveness of the above algorithm, Dr. Michael Rice created seven test signals without revealing the modulation type nor symbol rate and gave them to the author. A block diagram of how the signals were produced is shown in Figure 3.12. The signals were produced by a Quasonix L/S-band transmitter (Quasonix model number QSX-VMR-110-10S-20-40-VP-INET).

Figure 3.10: Percentage of correct decisions between PCM/FM and SOQPSK-TG when the transmitted signal is PCM/FM (top) and when the transmitted signal is SOQPSK-TG (bottom) when using a single FFT point for a decision.
Figure 3.11: Bit rate estimate variance when the transmitted signal is PCM/FM (top) and when the transmitted signal is SOQPSK-TG (bottom) when using a single FFT point for a decision.

The carrier frequency was set to 2245 MHz and the data length-32767 ($2^{15} - 1$) PN sequence. The transmitter is capable of producing both PCM/FM and SOQPSK-TG at arbitrary bit rates. The transmitted signal was attenuated and cabled to the input of the Cobham M/A-COM SMR 5550i receiver. The receiver output is a 70 MHz IF signal with a bandwidth of 20 MHz and constant output level of -5 dBm. The receiver IF output was connected to the Wideband Systems DRS 3300 data acquisition system. The sample rate was 100 Msamples/s. Each sample is 8 bits.

The signal recorded by the data acquisition system required some signal processing before it could be tested. A block diagram of the signal processing performed is shown in Figure 3.13. The signal needed to be shifted from the 70 MHz carrier frequency down to baseband. Since the
The sample frequency was 100 Msample/s, $\omega_0 = 0.6\pi$. The signal was then filtered with a length 100-FIR filter which was generated using the Parks-McClellan algorithm. The frequency response of this filter can be seen in Figure 3.14 and the impulse response can be seen in Figure 3.15.

The results of the blind estimates are shown in Table 3.1. The file names are those that were given to the author for the different test signals. The estimates are those that were produced by the Bianchi algorithm described in this chapter. The results for $\hat{\alpha}$ and $\hat{R}_b$ are the average of 100 runs of the algorithm across different segments of 32768 samples. The modulation estimates are what most of these runs determined. The modulation estimate was the same for every run using 32768 samples and there was very little variance in the bit rate estimate $\hat{R}_b$. Other tests with different sample sizes produced very similar results. When 8192 samples or less were used, a few runs, of the 100, estimated a different modulation type but $\hat{R}_b$ of the remaining runs remained the same. The actual results show that each test estimated the modulation type correctly. The true values of
Figure 3.14: Frequency response for the low pass filter used in the hardware test.

$R_b$ are shown in the last column in Table 3.1 and show that the estimates are very close to the actual values.
Figure 3.15: Impulse response for the low pass filter used in the hardware test.

Table 3.1: Estimates of Wideband test signals produced by Michael Rice.

<table>
<thead>
<tr>
<th>File Name</th>
<th>Modulation Estimate</th>
<th>$\hat{\alpha}$</th>
<th>$\hat{R}_b$ (Mbits/s)</th>
<th>$R_b$ (Mbits/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSN017-2A01.dat</td>
<td>SOQPSK-TG</td>
<td>0.049866</td>
<td>4.987</td>
<td>5.00</td>
</tr>
<tr>
<td>RSN018-2A01.dat</td>
<td>SOQPSK-TG</td>
<td>0.072385</td>
<td>7.239</td>
<td>7.25</td>
</tr>
<tr>
<td>RSN019-2A01.dat</td>
<td>PCM/FM</td>
<td>0.061084</td>
<td>6.105</td>
<td>6.12</td>
</tr>
<tr>
<td>RSN020-2A01.dat</td>
<td>SOQPSK-TG</td>
<td>0.095399</td>
<td>9.540</td>
<td>9.55</td>
</tr>
<tr>
<td>RSN021-2A01.dat</td>
<td>PCM/FM</td>
<td>0.031377</td>
<td>3.138</td>
<td>3.14</td>
</tr>
<tr>
<td>RSN022-2A01.dat</td>
<td>PCM/FM</td>
<td>0.049994</td>
<td>4.999</td>
<td>5.00</td>
</tr>
<tr>
<td>RSN023-2A01.dat</td>
<td>SOQPSK-TG</td>
<td>0.103029</td>
<td>10.303</td>
<td>10.3125</td>
</tr>
</tbody>
</table>
CHAPTER 4. PHASE CHANGES

Phase changes, as described in Section 2.5, could be used as a method of modulation recognition, but only if accurate phase changes can be collected. CPM signals are demodulated by analyzing the changes in phase from symbol to symbol. At the end of the symbol period, there are a finite number of states, called terminal phase states, that the phase can be in. Figures 4.1-4.3 show representations of these terminal phase states, and all the possible paths between them. These graphs are called “trellises” and demonstrate that there are many paths between the terminal phase states. Demodulators analyze these paths to decide what symbols were transmitted.

Finding the change in phase from one symbol to the next is possible if the bit-rate or symbol-rate of the signal is known and the samples of the received signal are taken exactly between symbols. This thesis does not address how to do this but instead uses a different signal model so that the changes in phase are the observations. Thus, the receiver observes

\[ y(t) = s(t) + n(t) \] (4.1)

and processes the observation to determine if \( s(t) \) is PCM/FM, SOQPSK-TG, or ARTM CPM. \( n(t) \) models the additive thermal noise and is a complex-valued Gaussian random process with zero mean and autocovariance function given by (2.2). The observed signal is sampled exactly at the end of each symbol period to produce the sample sequence \( y(iT_s) \) for \( i = 0, ..., N - 1 \). This gives

\[ y(iT_s) = |y(iT_s)|e^{j\theta(i)}. \] (4.2)

The phase of the sample, \( \theta(i) \), is one of the terminal phase states in the phase trellis. The series of observed phase differences, \( \Delta \theta_1, \Delta \theta_2, ..., \Delta \theta_N \), where \( \Delta \theta_i = \theta(i) - \theta(i - 1) \), is what the following identification methods use to make a decision.
Figure 4.1: Phase trellis for PCM/FM.

Figure 4.2: Phase trellis for SOQPSK-TG.
4.1 Closest Possible Phase Change

The first identification method involves comparing each individual phase change to a set of possible changes in phase. To do this, a baseline set of possible phase changes was made for each modulation type. This was done by analysis of the phase trellises shown in Figures 4.1-4.3. Let $\Pi_0$ be the set of all possible phase changes for PCM/FM, let $\Pi_1$ be the set of all possible phase changes for SOQPSK-TG, and let $\Pi_2$ be the set of all possible phase changes for ARTM CPM. For PCM/FM, we have

$$\Pi_0 = \{-0.7\pi, 0, +0.7\pi\}. \tag{4.3}$$

For SOQPSK-TG, there are 161 possible phase changes so that $\Pi_1$ has 161 members. This is too many to list. The elements of $\Pi_1$ are plotted from smallest to largest in Figure 4.4. For ARTM CPM, there are 128 possible phase changes. The members of $\Pi_2$ are plotted in Figure 4.5. show all the possible phase changes for the three modulations.

The classification technique proceeds as follows: The phase changes between successive samples of $y(t)$ are compared to the elements of $\Pi_0, \Pi_1,$ and $\Pi_2$ and the closest phase change from

![Figure 4.3: Phase trellis for ARTM CPM.](image)
Figure 4.4: Plot of all possible phase changes for SOQPSK-TG. The phase changes are sorted from least to greatest.

Figure 4.5: Plot of all possible phase changes for ARTEM CPM. The phase changes are sorted from least to greatest.
each set is found. The classifier bases its choice on how well the sequence of phase differences from each set match the observed sequence of phase differences. To be more precise, let

\[
r_{0,i} = \arg\min_{\phi \in \Pi_0} \{ (\phi - \Delta \theta_i)^2 \} \text{ for } i = 1, 2, ..., N, \tag{4.4}
\]

\[
r_{1,i} = \arg\min_{\phi \in \Pi_1} \{ (\phi - \Delta \theta_i)^2 \} \text{ for } i = 1, 2, ..., N, \tag{4.5}
\]

\[
r_{2,i} = \arg\min_{\phi \in \Pi_2} \{ (\phi - \Delta \theta_i)^2 \} \text{ for } i = 1, 2, ..., N. \tag{4.6}
\]

The squared error between \( r_{j,i} \) and each phase change \( \Delta \theta_i \) is accumulated for each modulation by

\[
E_0 = \sum_{i=0}^{N} (\Delta \theta_i - r_{0,i})^2,
\]

\[
E_1 = \sum_{i=0}^{N} (\Delta \theta_i - r_{1,i})^2,
\]

\[
E_2 = \sum_{i=0}^{N} (\Delta \theta_i - r_{2,i})^2.
\]

These values are used to make a decision by

\[
\text{modulation} = \begin{cases} 
\text{PCM/FM} & E_0 < E_1 \text{ and } E_0 < E_2 \\
\text{SOQPSK-TG} & E_1 < E_0 \text{ and } E_1 < E_2 \\
\text{ARTM CPM} & E_2 < E_0 \text{ and } E_2 < E_1.
\end{cases} \tag{4.7}
\]

The simulated results for this method are shown in Figure 4.6. Each line in the plot corresponds to the percentage of correct decisions for each modulation type shown over a range of \( E_b/N_0 \). The plot shows that correct decisions using the closest possible phase change method can be made above 45 dB \( E_b/N_0 \). Below this level, where the data is too noisy, the decision favors ARTM CPM. This is due to the set of baseline phase changes \( \Pi_2 \) for ARTM CPM. The possible phase changes in this set are spread out so it is more likely that a noisy value will be closer to one of these.
Figure 4.6: Percentage of correct decisions using the closest possible phase change algorithm. Each line in the plot corresponds to the type of modulation that was transmitted.

4.2 Histograms and K-L Distance

For a long set of phase changes $\Delta \theta_1, \Delta \theta_2, \ldots, \Delta \theta_N$, some phase changes are more common than others. This is because there is more than one sequence of symbols that can create it. The more common changes in phase can be shown by a histogram. Figures 4.7 through 4.9 show the histograms for a long sequence of simulated data. To make them, a string of phase changes, without noise, was generated for each modulation type. Each phase change was placed into a bin in the histogram which are all equally spaced. At the end of the sequence, the number of phase changes placed in each bin were counted and the number divided by the total number of phase changes. This gives the probability that any given phase change, $\Delta \theta_i$, will fall into that bin in the histogram for the given modulation type. These histograms can then be viewed as a probability
density function (pdf) for the phase changes. Let

\[ p_0(k) = Pr(\Delta \theta = \Delta \theta_k \text{ for PCM/FM}) \text{ for } k = 0, 1, ..., M - 1, \] (4.8)

\[ p_1(k) = Pr(\Delta \theta = \Delta \theta_k \text{ for SOQPSK-TG}) \text{ for } k = 0, 1, ..., M - 1, \] (4.9)

\[ p_2(k) = Pr(\Delta \theta = \Delta \theta_k \text{ for ARTM CPM}) \text{ for } k = 0, 1, ..., M - 1 \] (4.10)

which correspond to each individual histogram bin selected by the index \( k \). \( M \) is the number of histogram bins used between \(-\pi\) and \( \pi\). Let

\[ p_0 = [p_0(0), p_0(1), ..., p_0(M - 1)], \] (4.11)

\[ p_1 = [p_1(0), p_1(1), ..., p_1(M - 1)], \] (4.12)

\[ p_2 = [p_2(0), p_2(1), ..., p_2(M - 1)] \] (4.13)

be the vectors of the histogram bins for PCM/FM, SOQPSK-TG, and ARTM CPM respectively. Each modulation has a different set of possible phase changes as described in the previous section: 3 for PCM/FM, 161 for SOQPSK-TG, and 128 for ARTM CPM. The bins that do not include a possible phase change will be zero. In order to place each possible phase change into its own bin, the bins need to be very small because many can be very close together. A more course histogram with larger bins may include several possible phase changes in the same bin. Both can give good results. Examples of more course histograms are shown in Figures 4.7, 4.8 and 4.9 because they are easier to see than the smaller bins, but similar shapes result from using smaller bins.

For identification of an unknown set of phase changes, \( \Delta \theta_1, \Delta \theta_2, ..., \Delta \theta_N \), a histogram of this set needs to be made first. It is made by placing each element into a bin, and counting the number placed in each bin. The count for each bin is then divided by the total number of phase changes to create a histogram in the same way the baseline histograms were generated previously. Let \( q \) correspond to the histogram generated from the received sequence of phase changes and \( q(k) \) correspond to each normalized histogram bin. Then, this new histogram must be compared to the three known histograms to determine which is more similar. The Kullback-Leibler distance is a
Figure 4.7: Histogram of phase changes between bits for PCMF/FM. Each bin is $\pi/40$ wide.

Figure 4.8: Histogram of phase changes between bits for SOQPSK-TG. Each bin is $\pi/40$ wide.
Figure 4.9: Histogram of phase changes between bits for ARTM CPM. Each bin is $\pi/40$ wide.

A good method for doing this, which is given by

$$D(p_j, q) = \begin{cases} \sum_{k=0}^{M} p_j(k) \log_2 \frac{p_j(k)}{q(k)} & p_j(k) \neq 0 \\ 0 & p_j(k) = 0 \end{cases}$$

where $j \in \{0, 1, 2\}$ for the three baseline histograms. The smaller the value for $D$, the more similar the two distributions are. The decision is then

$$D(p_j, q) = \begin{cases} \min(D(q, p_0), D(q, p_1), D(q, p_2)) = D(q, p_0) & \text{PCM/FM} \\ \min(D(q, p_0), D(q, p_1), D(q, p_2)) = D(q, p_1) & \text{SOQPSK-TG} \\ \min(D(q, p_0), D(q, p_1), D(q, p_2)) = D(q, p_2) & \text{ARTM CPM} \end{cases}$$

(4.15)

Results of the simulations of this method are shown in Figures 4.10 and 4.11. Each line in the plot corresponds to the percentage of correct decisions for each modulation type shown over a range of $E_b/N_0$. Figure 4.10 used very small bins so that each possible phase change was placed in its own
bin. Figure 4.11 shows the results from using larger bins so many possible phase changes were bunched together. The plots show that correct decisions using the histogram with the K-L distance method can be made above 30 dB $E_b/N_0$ for either size of bin. Both sets preferred a decision for SOQPSK-TG in a high amount of noise which is probably because the histogram for SOQPSK-TG covers a larger range of values than the other two, even though it has gaps in between.

The difference between them is in the size of the data set needed to make these decisions. When any bin in the received histogram is left empty when the corresponding bin in the baseline histogram has a value, the K-L distance between these two distributions is infinity. When the bins are very small and each possible phase change has its own bin, every possible phase change needs to be present in the received signal to make a correct decision. This problem is complicated more in the presence of noise, when it only requires a small amount of noise to push the received phase change into the wrong bin. In order to ensure that every bin in the histogram made from the recieved data corresponding to a non-zero bin in the baseline histograms, a very long set of data is needed. In this case, 100,000 symbols were used for the small histogram bins, when only 3,000 symbols were needed for the larger bins.

### 4.3 Conclusions

Figures 4.6 and 4.11 show that for the closest possible phase change method, correct decisions can be made above 45 dB $E_b/N_0$ while correct decisions can be made using the K-L distance method above 30 dB $E_b/N_0$ with longer sets of data required for smaller sizes of bins. Clearly, the K-L distance method is far superior to the closest possible phase change method. These methods have the advantage that they work for all three modulation types as long as the symbol rate of the signal is already known. It is also necessary to sample the phase at the end of the symbol period. These challenges would need to be overcome in order to make this a useful method but it may be helpful in future work.
Figure 4.10: Percentage of correct decisions using the histogram with K-L distance algorithm. Each line in the plot corresponds to the type of modulation that was transmitted. The data was generated for histograms with bins $\pi/10000$ wide. The test histogram from the simulated data was formed from 100,000 symbols at 20 samples/symbol. Each data point was made from 100 trials.
Figure 4.11: Percentage of correct decisions using the histogram with K-L distance algorithm. Each line in the plot corresponds to the type of modulation that was transmitted. The data was generated for histograms with bins $\pi/40$ wide. The test histogram from the simulated data was formed from 3,000 symbols at 20 samples/symbol. Each data point was made from 1000 trials.
CHAPTER 5. CONCLUSIONS

The goal of this thesis is to distinguish PCM/FM, SOQPSK-TG and ARTM CPM without any prior information except the carrier frequency. It explored modulation recognition methods that have been applied to other modulation types as possible methods to accomplish this task. A likelihood based approach to this problem was formulated and was found to be intractible. Several statistical features (the variance, skewness and kurtosis) of the amplitude, phase, and instantaneous frequency were explored as possible distinguishers. These features were too similar across all three modulations, or varied too much with noise and symbol-rate, to be useful at distinguishing these modulations.

A successful method was found by using a blind estimator developed by Bianchi to distinguish between PCM/FM and SOQPSK-TG. This method was also able to give an accurate estimate of the bit-rate. Another successful method was found in analysis of the phase changes that take place between symbols in CPM. This method could distinguish between PCM/FM, SOQPSK-TG and ARTM CPM as long as symbol timing synchronization has been achieved. Detailed conclusions of these two methods are given in the following two sections.

5.1 Bianchi Conclusions

PCM/FM and SOQPSK-TG can be reliably distinguished using the Bianchi method described in Section 2.4 for a sufficiently high signal-to-noise ratio and search resolution. (For the simulation parameters presented here, this signal-to-noise ratio threshold is about 20 dB for an observation length of 16384 samples.) As a byproduct, an estimate of the bit rate is also produced. This information (the classifier result and bit rate estimate) can be used to perform pre-flight or pre-launch checks to ensure the telemetry transmitter is properly configured for these two modulation types. This method, however, is unable to make any kind of classification or symbol rate estimate for ARTM CPM.
Several variations on the algorithm were also presented. These variations were: changing the order of interpolation, using an absolute value instead of an absolute value squared, not normalizing the received signal, and leveraging a single FFT point in the decision making. It was found that these variations either did not effect the accuracy of the classifier, or degraded performance. The algorithm was also tested on data captured from hardware and results of these tests were given and show that it also works well on hardware.

5.2 Phase Trajectory Conclusions

All three modulation types can be distinguished by analysis of the changes in phase between symbols with sufficiently high $E_b/N_0$. Analysis of these phase changes requires prior knowledge of the symbol-rate of the signal and that samples be taken at the end of each symbol period. This thesis does not describe how this sampling might be accomplished. The closest possible phase change method was effective above 45 dB and the histogram and K-L distance method is effective above 30 dB. It was also found that the size of the histogram bins can have an effect on the number of samples required to make correct decisions between the modulations. If the bins are small, then a large number of samples are needed where larger size bins need fewer samples.

5.3 Suggestions for Future Work

The Bianchi method can reliably distinguish between PCM/FM and SOQPSK-TG but more could be done to improve the algorithm described in this paper. This paper did not attempt to compensate for carrier frequency offset, but adjustments may be developed to fix this problem. The paper by Bianchi [13] gives some methods to do this. This may have effects on the performance of this algorithm which would be interesting to explore.

Extracting modulation decisions from the changes in phase could be a reliable method if the symbol rate can be estimated first. If this is found, then the performance of the algorithm in this thesis could be explored further to find the optimal number of histogram bins to use. Also, with an accurate estimate of symbol-rate, or given this information a priori, techniques to capture samples exactly at the end of the symbol period could be explored as well as how this sampling would affect this algorithm.
It may also be interesting to apply the techniques in this paper to other types of CPM modulations that were not described here. The Bianchi paper was only applied to full-response CPM modulations but it worked well for PCM/FM and SOQPSK-TG. Other CPM modulations may work as well. If some methods work for some types, decision trees could be developed to classify a larger set of modulations.

Other work could be explored under the basis that more knowledge of the received signal is known such as the symbols of the signal. This may be the case if the transmitter is placed into a verification mode and transmits a predetermined sequence of data. This may open up other methods that were discarded in Chapter 2 because that was not the goal of this thesis.
REFERENCES


