

# A comprehensive view into MPSK modulation classification

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**Abstract.** This paper provides a relative comprehensive overview on current modulation classification of MPSK from both the likelihood-based perspective and the feature-based perspective. Traditional methods based on maximum likelihood (ML) method mainly diverges in the way how unresolved parameters from the received signal are viewed. Some recent work adopting feature recognition such as SVM-based and Deep Learning-based classifying algorithms are also introduced. Fundamental equations are also provided for each method. This paper makes comparison among different methods in each section and explained the preferred utilization circumstance of each, aiming to help readers find the best algorithm in each of their specific case. Moreover, advantages and disadvantages of different algorithms are clearly stated for the readers' information. Based on the pros and cons, it is also suggested for readers to develop new compound algorithms of better functionality for further research.

**Keywords:** modulation classification, PSK, maximum-likelihood classification, feature extraction.

## 1. Introduction

Signal modulation is an inseparable and characteristic part in digital communication. While under different circumstances, modulation types can be varied and unique, it is of vital importance that one first correctly classifies the modulation type before demodulating and analysing the signal.

This paper presents comprehensive overview on modulation classification in the scope of common MPSKs (i.e., BPSK, QPSK and 8PSK). Classically, there are two main method branches in MC. One is based on the ML method, which the modulation type is set as unknown variable to be determined using spectral parameters. Sapiiano and Martin proposed the method of using Average Likelihood Ratio Test (ALRT) in classification of PSK [1]. Hong and Ho proposed a method in classifying PSK using unbalanced factor and Generalized Likelihood Ratio Test (GLRT) [2]. Panagiotou etc. pushed the research even forward by presenting classification algorithms using Hybrid Likelihood Ratio Test (HLRT) [3], and found its performance could noticeably outstand the ALRT-based method in accuracy. While the ML method has advantage in comparing different classifiers and achieving the optimal more easily, it suffers from the high complexity for both the algorithm and the approximation.

The other method branch in MC is based on feature recognition. There are lots of characteristic features to consider, some such as time-domain parameters [4], spectral analysis [5], wavelet transform features [6] are commonly extracted for modulation classification of MPSK. Next, classifiers based on Decision Tree [7], Neural Networks (NN) [8] and Support Vector Machines (SVM) [9-11], are adopted in further recognition of the features extracted.

The organization of this paper will be as follows: Section 1 is a brief introduction followed by the PSK modulation analysis in Section 2. Section 3 and 4 will present current methods of PSK modulation classification from likelihood and feature aspects respectively. Conclusions are provided in Section 5.

## 2. Signal model of MPSK

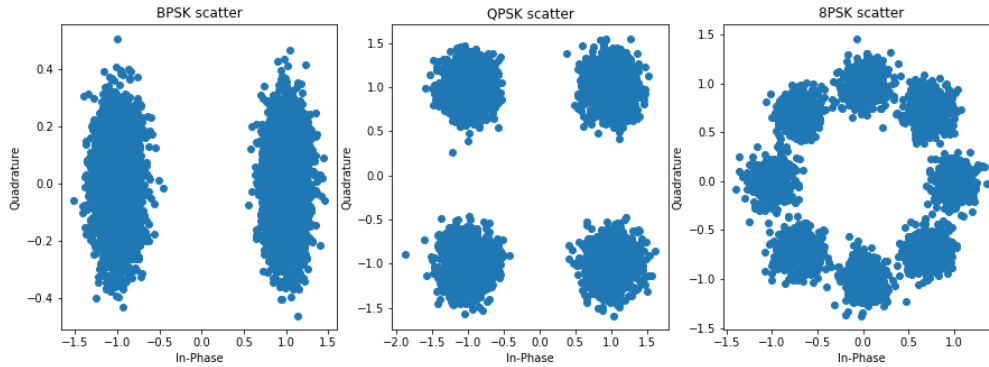
For the modulation of MPSK ( $M = 2, 4, 8$ ), baseband signals will modify the phase of the carrier wave, frequency and amplitude of the carrier wave will not be changed during transmission. The MPSK-modulated signal is depicted as:

$$S_{MPSK} = \sum_n g(t - nT) \cos(2\pi f_c t + \varphi_n) \quad (1)$$

In the above expression,  $n$  symbols are being transmitted,  $g(t)$  is the rectangular pulse function,  $T$  is the duration of each symbol,  $f_c$  is the frequency of the carrier wave.  $\varphi_n$  represents the phase of the carrier wave with the following correspondence:

$$\varphi_n = \frac{2\pi(n-1)}{M}, n = 1, 2, \dots, M \quad (2)$$

Another way of understanding the MPSK-modulation is through constellation maps as depicted in Figure 1, where each cluster of dots represents a specific phase.



**Figure 1.** Scatter plots of MPSK-modulated signals at SNR = 15 dB.

## 3. Likelihood-based methods

### 3.1. ML classification

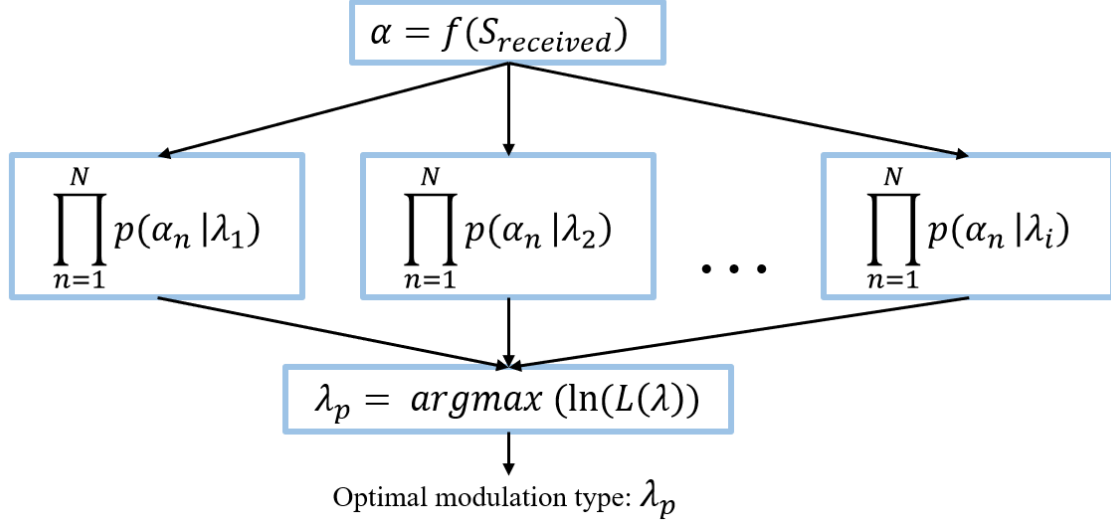
The ML ratio test is a multi-variable hypothesis testing process based on cost minimization. Let  $\lambda_i, i = 1, 2, \dots, I$ , denote the different modulation types to be classified,  $\alpha_n, n = 1, 2, \dots, N$ , denote different observations, then the ML function can be expressed as follows.

$$L(\lambda_i) = \prod_{n=1}^N p(\alpha_n | \lambda_i) \quad (3)$$

Taking the natural logarithm on both sides, the optimal modulation type will be classified through the following expression.

$$\ln(L(\lambda_p)) \geq \ln(L(\lambda_q)), \quad p \neq q \text{ and } p, q \in \{1, 2, \dots, I\} \quad (4)$$

A clear flow chart showing the above process is demonstrated in Figure 2. Observations  $\alpha_n$  are derived based on the received signal, while the resulting optimal modulation type  $\lambda_p$  is recognized using argmax function.



**Figure 2.** Flow chart of the ML ration test.

Assuming all signal and noise parameters are known, Wei and Mendel proposed a formula in assessing error probability for ML classifiers [12]. Conclusion is also drawn that ML classifier can have optimal performance with zero error when infinite symbols are available [12].

### 3.2. ALRT, GLRT and HLRT

In real life, however, under non-cooperative communications, signal parameters such as mean or probability density function are hardly known. When such parameters are treated as random variables, it is the ALRT. In the scope of PSK classification, ALRT is proven to have slight advantage over using DFT of phase histograms [1, 13]. When compared with quasi-Log-Likelihood Ratio (qLLR) [14] classifier, while the complexity of the two methods is close, ALRT also has slight advantage in error rate [1].

When the unresolved parameters are handled as unknown variables under maximum likelihood estimation, GLRT takes place [2]. In classifying BPSK and unbalanced QPSK, the unbalanced factor is taken into account with a maximum likelihood estimate, this attempt has great advantage over not considering the unbalanced factor at high SNR [2]. Comparing with ALRT, although GLRT need no pre-assumptions, it requires a maximum estimation procedure [3].

HLRT can be viewed as a hybrid of ALRT and GLRT. While one part of the unknown parameters is handled to be random, the rest are thought to be unknown [3]. For example, Panagiotou et al. proposed the Average Data Maximum Phase (ADMP) [3], and its performance is proven much better than the ALRT-based methods of qLLR [14].

## 4. Feature-based methods

### 4.1. Feature extracting

**4.1.1. Signal parameter features.** Traditional features include the instantaneous amplitude, phase and frequency in time-domain. Let  $\hat{s}(t)$  denote the Hilbert transformation of received signal  $s(t)$ . Then the instantaneous amplitude, phase and frequency are expressed in Equations (5), (6), (7) respectively.

$$A(t) = \sqrt{s^2(t) + \hat{s}^2(t)} \quad (5)$$

$$\varphi(t) = \tan^{-1} \frac{\hat{s}(t)}{s(t)} \quad (6)$$

$$f(t) = \frac{1}{2\pi} \frac{d}{dt} \varphi(t) \quad (7)$$

A more generally adopted feature set nowadays is proposed by Bagga and Tripathi, using  $\gamma_{max}$ ,  $\sigma_{aa}$ ,  $\sigma_{ap}$ ,  $\sigma_{dp}$  and  $\sigma_{af}$  [4]. Of the five features,  $\gamma_{max}$  can serve to differentiate PSK from FSK, while  $\sigma_{aa}$  can differentiate ASK from PSK [4].  $\sigma_{ap}$  and  $\sigma_{dp}$ , which represent the absolute and direct instantaneous phases respectively, can be of crucial importance in classifying within the class of PSK since phase is the parameter being modified to different orders [4]. These features are easily extracted and are not based on prior assumption, however, they are easily distracted by noise and is dependent on the threshold of the later classifier, so to achieve acceptable error rate, high SNR environment is still preferred.

**4.1.2. Spectral features.** When applying non-linear transform to digital signals, different modulation types may result in differences of occurrences, positions and magnitudes of the spectrum. Square spectrum is the power spectrum after the original signal is squared. Strong spectrum is visible only to signals with  $\pi$  jumps in the carrier wave, such as BPSK signals [5]. This is similar with quartic spectrum, which represents the power spectrum to the power of four. The quartic spectrum can identify the QPSK, since there will be discrete spectrum at frequency zero [5]. To sum up, the classification of MPSK can be easily achieved by analyzing the square spectrum and quartic spectrum to see whether discrete spectrum near zero frequency exists. Though this method is convenient and less complex, there is still consideration on the threshold value in judging whether discrete spectrum exist near zero frequency.

**4.1.3. Wavelet transform features.** Wavelet transform is widely adopted in modulation classification due to its adaptability in providing a window that can be changed with frequency [6]. In the following, Haar wavelet transform will be adopted. For different types of modulations, different expressions are available using the magnitude of Haar continuous wavelet transform (CWT). An example expression of MPSK is provided below [6]:

$$CWT_{MPSK}(a, \tau) = \frac{4\sqrt{S}}{j\sqrt{a}\omega_c} \sin^2\left(\omega_c \frac{a}{4}\right) e^{j(\omega_c \tau + \theta_c + \varphi_i)} \quad (8)$$

In Equation 8,  $a$  is the scale,  $\tau$  is the translation,  $S$  denotes power of the received signal,  $\omega_c$  and  $\theta_c$  denote parameters of the carrier. The amplitude value T1 and frequency value T2 can be extracted, with each being different for different modulation types, (e.g., T1 for MPSK is 1, T2 for MPSK is 1) [6]. With a specific threshold range, the modulation type can thus be classified. However, with this method, high SNR is still demanded while it is difficult to tell between different types of PSK, further improvements of classification within the PSK class can focus on the instantaneous phases and their differences [6].

**4.1.4. Higher-order statistics (HOS).** HOS is another method frequently used since it can reflect the constellation diagram distribution and it is resistant to noise [15]. HOS method extracts feature mainly through cumulant of the second or fourth order. HOS consists two parts, Higher-order Matrix (HOM) and Higher-order Cumulant (HOC). For the received signal, some commonly used formulas of HOC are as follows:

$$C_{20} = M_{20} \quad (9)$$

$$C_{21} = M_{21} \quad (10)$$

$$C_{40} = M_{42} - 3M_{20}^2 \quad (11)$$

$$C_{42} = M_{42} - M_{20}^2 - 2M_{21}^2 \quad (12)$$

The above HOCs can be calculated and represented as expressions of the signal energy  $E$ . As the parameters are different for BPSK, QPSK, and 8PSK, they can thus be classified. Swami developed a hierarchical classification scheme and adopted fourth order cumulants on a baseband with  $N$  samples, finding this method especially effective with complexity of  $O(N)$  [15].

#### 4.2. Feature classification

4.2.1. *Decision trees.* A rather simple method in classifying different modulation types is through adopting decision trees. At each node, among all features extracted, only the feature maximizing information gain will be chosen as the attribute test [7]. Decision trees have low computing complexity, need relatively fewer data, and have good performance in accuracy. However, it may be highly dependent on the features and dataset, making it less stable. A possible solution may be using multiple decision trees together and forming a random forest.

4.2.2. *NN.* Neural networks mainly consist of three parts. Apart from the input and output layers, the most important component is the hidden layers, whose nodes each has their own computing expression with each term being the product of weight and input. Only when the node's expression reaches a certain threshold will be activated and pass the value on to the next layer, and eventually to the output layer. The number of hidden layers and neurons within each layer greatly affects overall accuracy performance, which may result in overfitting. A special case when two or more hidden layer is the Deep Neural Network (DNN). Researches show that DNN networks own great flexibility in the detection of different modulation types and that it has accuracy advantage over traditional NN especially in Doppler fading channels [8].

4.2.3. *SVM.* The goal of SVM is to construct a hyperplane that can separate two groups of data with maximum geometric distance to each. Kernel tricks can also be adopted for non-separable data, making it a non-linear classifier. While SVMs were originally for binary classification, there are mainly two ways in multiple classification. The first solution is combining several binary SVM together, but unclassifiable region will arise due to discrete decision [9]. The second solution is multi-class support vector machines (MSVM) such as one-against-one and one-against-all methods [10]. Classifier models were also proposed in handling unclassifiable region combining theories with directed acyclic graphs, which not only gained advantage in accuracy but also retained a fast speed [11]. SVM have greater generality and can find the global extremes rather than the local extremes which shows its advantage over traditional NN.

#### 5. Conclusion

This paper reviewed past development of modulation classification through both the likelihood-based method and feature-based method. According to the above research, in various ways can the signal features be constructed, but the final classifiers are still traditional techniques in Machine Learning. While in this area, the research of Decision Trees and NN started the earliest, currently advanced methods are mainly based on Deep Learning and SVM training. Both models are complex to train. SVM have better performance with little data and fewer modulation types, while Deep Learning and NN are more capable and preferred when abundant training data and various modulation types are present. Potential future research may lie in seeking a harmonic balance combining multiple classifiers so to have optimal performance at less cost.

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