Likelihood Methods For MPSK Modulation Classification
Chung-Yu Huang and Andreas Polydoros, Fellow, IEEE

Abstract—New algorithms based on the Likelihood Functional (LF) and approximations thereof are proposed for the problem of classifying MPSK modulations in additive white Gaussian noise. Previously introduced classifiers for this problem are theoretically interpreted as simplified versions of the ones in here. The performance of a single-term approximation to the optimal LF classifier is evaluated analytically and is shown to be very close to that of the optimal. Furthermore, recursive algorithms for the implementation of this new quasi-log-Likelihood-Ratio (qLLR) classifier are derived which imply no significant increase in classifier complexity. The present method of generating classification algorithms can be generalized to arbitrary two-dimensional signal constellations.

I. INTRODUCTION

SIGNAL classification is a branch of non-cooperative communication theory, which brings together several aspects of classical - or cooperative - communication theory: signal detection, parameter estimation, channel identification and tracking, to name a few, in an environment which may vary between extremes: no significant noise in the best of circumstances, to very messy, with additive white Gaussian noise (AWGN), fading, multipath, and interference present at the same time. In a particular form it can be cast as a multiple-hypothesis statistical testing problem, having to do with choosing or identifying one type of modulation from a known set of candidates, embedded in the above-mentioned noisy and distorting environment.

The two standard approaches to modulation classification so far have been (a) the pattern-recognition or feature-extraction approach, and (b) the memoryless-nonlinearity-and-filtering approach. The first relies on the classical concept of “feature”, whereas the second is based on the observation that raising the observed waveform to an appropriate power and filtering at the right spectral band produces different levels of measurable power, depending on the modulation.

For MPSK modulation classification, in particular, the typical extracted feature is the information-bearing phase [2], [3], or the difference of such consecutive phases [1], which are then either used in a histogram-based discriminating test, i.e., where the presumed number \( M \) in the phase modulation under classification (a power of 2, in this problem) is the number of distinguishable modes in the histogram, or in moment-related statistics.

In the second approach, an \( M^{th} \)-law memoryless non-linearity is employed for classifying between MPSK and \( M^{th} \)-PSK with \( M' > M \). This is done by detecting the presence or absence of a spectral line at the \( M \)-times-carrier-frequency spectral band. In the same broad category we can include spectral-correlation based rules [4], which can be interpreted as generalized quadratic processing schemes and have been shown to be equivalent to a low-SNR version of the likelihood ratio test. However, it does not appear that such spectral correlation based rules can distinguish between MPSK signals for \( M \geq 4 \), unless implemented as an intermediate step for higher-order \( (M^th \text{-law}) \) processing.

A novel approach, called decision-theoretic or the likelihood method was recently introduced in [5] and applied to the specific problem of classifying between BPSK and QPSK signals. The particular concept promoted therein is that likelihood functional (LF) or, equivalently, the log-likelihood functional (LLF) of the observed waveform, conditioned on the embedded digitally modulated random signal, contains all the necessary information for a variety of inference tasks (signal detection, classification and parameter estimation), so that it should constitute the basis for any further processing in an optimal or quasi-optimal (i.e., after some simplification) sense.

The main thrust of the present paper is to generalize the likelihood method for classifying any MPSK signal in AWGN; preliminary results on this problem can be found in [6] and [7]. It will be shown that this approach provides a general framework within which one can interpret previously known structures and create new ones. A fast recursive algorithm is introduced and the performance of the proposed LF-based classifiers in terms of the resulting correct classification probability (CCP) is computed and compared to that of the currently known MPSK classifiers.

Extensive simulation results are also presented which verify the analytical results (whenever available) and provide performance estimates for the cases where analysis is cumbersome (in particular, the optimal rule).

The paper is organized as follows: The signal models and assumptions are introduced in Section II. Section III derives the LLF for an MPSK signal. Then, classification algorithms are derived starting from this LLF expression for three different types of the underlying modeling environment. In Section IV, the theoretical CCP performance

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of the LF-based classifiers is analyzed, and an efficient recursive implementation for the proposed algorithms is presented. Sections V derives some other suboptimal MPSK classifiers by simplifying the LF-based rules, and relates previously known MPSK classifiers to those suboptimal classifiers. Finally, the numerical performance of all MPSK classifiers and associated comparisons are presented in Section VI.

II. SIGNAL MODELS AND ASSUMPTIONS

Let the received waveform \( r(t) \), \( 0 \leq t \leq NT_s \), be the sum \( r(t) = s(t) + n(t) \), where \( T_s \) is the symbol duration known to the receiver. \( N \) is the number of observed symbols (bauds) and \( n(t) \) is the standard AWGN with two-sided power spectral density (PSD) of \( N_0/2 \) W/Hz. The signal part \( s(t) \) is modeled as

\[
s(t) = Re\{\sqrt{2S} \sum_{k=1}^{N} e^{j\theta_k} p(t - (k-1)T_s - \varepsilon) e^{j(2\pi f_c t + \varepsilon)}\}
\]

where \( \theta_k \in \{2\pi i/M; i = 0, \ldots, M-1\} \) is the information-bearing phase sequence of an MPSK signal and the baseband pulse \( p(t) \) of duration \( T_s \) sec. satisfies \((T_s)^{-1} \int_{-T_s/2}^{T_s/2} p(t)^2 dt = 1\). Let

\[
\gamma_s \equiv \frac{ST_s}{N_0}
\]

denote the input or symbol SNR. The signal power \( S \), the pulse duration \( T_s \), the input SNR \( \gamma_s \), and the carrier frequency \( f_c \) will be assumed known throughout the paper.

Three different modeling environments are explored in this paper. The first is the coherent and synchronous environment (CSE), wherein the carrier phase \( \theta_c \) and the symbol timing offset \( \varepsilon \) are presumed known to the receiver (or derivable with minimal estimation loss via standard tracking-loop mechanisms [10]); their values will be set to zero without loss of generality. In the noncoherent and asynchronous environment (NCAE), both of them are unknown and modeled as random variables (r.v.) uniformly distributed in \([0, 2\pi]\) and \([0, 1]\), respectively. The noncoherent and synchronous environment (NCSE) is an intermediate case where it is assumed that \( \varepsilon = 0 \) and \( \theta_c \) is an r.v. with the above distribution. Based on the assumed prevailing model, which reflects different levels of classifier complexity and/or status, we can properly derive the associated LLF as per the following Section III.

III. LF-BASED MPSK CLASSIFICATION RULES

The LLF of the received waveform \( r(t) \) in AWGN, given the signal \( s(t) \), is defined as\(^1\)

\[
l(r(t)) = \ln \lll \exp\{\frac{1}{N_0} \int_{-T_s/2}^{T_s/2} r(t) \cdot s(t) dt\} \rrr > \gamma_s > \gamma_c
\]

where \( > \gamma_s, > \gamma_c \) and \( > \gamma_c \) denote averaging over \( \theta_c, \theta_c \)

\(^1\)The definition in (3) neglects the term related to the signal energy. This is a constant which is common to all LLF's herein, thus immaterial in further development.

and \( \epsilon \), respectively. Substitution of the MPSK signal (1) into the LLF definition (3) yields

\[
l_{MPSK} = \ln \lll \exp\{\frac{1}{N_0} \int_{-T_s/2}^{T_s/2} r(t) \cdot s(t) dt\} \rrr > \gamma_s > \gamma_c
\]

is the complex envelope of the normalized pulse-matched filter output at the indicated time instant. The normalizing factor \( 2\sqrt{N_0T_s} \) in (5) is inserted in order to make the corresponding variances \( \text{Var}[r_{I,k}(\epsilon)] = \text{Var}[r_{Q,k}(\epsilon)] = 1 \).

Let us suppose that we wish to construct a test for testing the hypothesis \( H_1 = \text{MPSK} \) versus \( H_2 = \text{M'PSK} \) for a specific \( M' \succ M \). The optimal classification rule for such a binary hypothesis test is simply\(^2\)

\[
\frac{l_{MPSK} - l_{M'PSK}}{M'PSK} \geq \lambda_{MPSK}(Q)\leq \text{Threshold}
\]

Because of its complicated structure, it does not seem practical to try to implement exactly the above optimum rule. To simplify, we make a small-SNR assumption by letting \( \gamma_s \ll 1 \). By use of the two approximations

\[
cosh(x) \cong \sum_{p=0}^{\infty} \frac{x^{2p}}{(2p)!}
\]

for a small number \( x (x \ll 1) \) in (4), we arrive at the low-SNR approximate LLF

\[
\lambda_{MPSK}(Q) = \ln \lll \exp\{\frac{1}{N_0} \int_{-T_s/2}^{T_s/2} r(t) \cdot s(t) dt\} \rrr > \gamma_s > \gamma_c
\]

\(^2\)If the prior probabilities of the individual hypotheses are known, a Bayes test can, in principle, be constructed, which will affect the threshold setting by a factor. In this paper, we do not assume any such knowledge and proceed in a Maximum Likelihood (ML) spirit, namely, choose the hypothesis for which the conditional likelihood of the observation is largest.
performance. Note that a smaller $Q$ will always provide a simpler structure. The above LLF expression can be simplified via use of the identity

$$\left(\text{Re}\{z\}\right)^{2p} = \frac{(2p)!}{2^{2p}(p!)^2} \cdot |z|^{2p} + \frac{1}{2^{2p-1}} \cdot \sum_{m=1}^{p} \binom{2p}{p-m} |z|^{2(p-m)} \text{Re}\{z^{2m}\}$$

which becomes

$$\lambda_{\text{MPSK}}(Q) = \ln < \exp\left\{ \sum_{p=1}^{Q} \frac{1}{(p!)^2} \cdot \left(\frac{7\pi}{2}\right)^p \sum_{m=1}^{p} |f_k(e)|^{2p} \right\} >_e$$

$$+ \ln < \exp\left\{ \sum_{p=1}^{Q} \frac{1}{2} \sum_{m=1}^{N} \frac{2}{(p-m)!} |f_k(e)|^{2p} \right\} >_e$$

$$\cdot |\text{Re}\{\eta_{\text{M}}(M)\sum_{k=1}^{N} |f_k(e)|^{2(p-m)} |f_k(e)|^{2m} e^{j2\pi e_k m}\} >_e$$

with

$$\eta_{\text{M}}(M) = \frac{2}{M} \sum_{i=0}^{M/2-1} e^{j2\pi i \frac{M}{2}} , \quad 1 \leq m \leq Q$$

We observe that $\eta_{\text{M}}(M)$ is the only term which depends on the different hypotheses. As per eq. (6), a suboptimal classification rule for MPSK versus $M'$PSK with $M' > M$ is to compare the following difference

$$\lambda_{\text{MPSK}}(Q) - \lambda_{\text{M'PSK}}(Q) = \ln < \exp\left\{ E(M, Q) \right\} >_e$$

$$<< \exp\left\{ E(M', Q) \right\} >_e$$

$$<0$$

$$\text{to a threshold, where}$$

$$E(M, Q) = \sum_{p=1}^{Q} \frac{1}{2} \sum_{m=1}^{p} \frac{1}{(p-m)!} |f_k(e)|^{2p} Re\{\eta_{\text{M}}(M)\}$$

$$\sum_{k=1}^{N} |f_k(e)|^{2(p-m)} |f_k(e)|^{2m} e^{j2\pi e_k m}$$

To assess the behavior of the discriminating coefficient $\eta_{\text{M}}(M)$ in eq. (12), we note that $e^{j2\pi i} = 1$ for any integer $n$, which implies that

$$\eta_{\text{M}}(M) = \left\{ \begin{array}{ll} 1, & m = \frac{1}{2}M, \frac{3}{2}M, 2M, \cdots \\ 0, & \text{elsewhere} \end{array} \right.$$

and

$$\eta_{\text{M'}}(M') = \left\{ \begin{array}{ll} 1, & m = \frac{1}{2}M', \frac{3}{2}M', 2M', \cdots \\ 0, & \text{elsewhere} \end{array} \right.$$

Since $M'/2 > M$ by definition, it can be shown that, whenever $Q < \frac{M}{2}$,

$$\lambda_{\text{MPSK}}(Q) = \lambda_{\text{M'PSK}}(Q)$$

$$\lambda_{\text{MPSK}}(Q) = \ln < \exp\left\{ \sum_{p=1}^{Q} \frac{1}{(p!)^2} \left(\frac{7\pi}{2}\right)^p \sum_{m=1}^{p} |f_k(e)|^{2p} \right\} >_e$$

Thus, the smallest value of $Q$ which results in a non-trivial classification rule is $Q = M/2$. If we define $q_M \triangleq \lambda_{\text{MPSK}}(M/2) - \lambda_{\text{M'PSK}}(M/2)$, we arrive at

$$q_M = \ln < \exp\left\{ \frac{2}{M!} \sum_{k=1}^{N} |f_k(e)|^{2M^2} \right\} >_e$$

We now observe that this answer (including the corresponding threshold, i.e., the total test) holds for any $M' > M$. Thus, within the class of single-term qLLR's, this results in a Uniformly Most Powerful (UMP) test for the comparison of the hypothesis $H_1$ defined above versus the composite test $H_2: \text{M'PSK}$ for any $M' > M$. This is because all M PSK waveforms result in the same output pdf, once processed by the $q_M$ rule. We can further simplify $q_M$ based on the different communication environment assumptions; we explore those below.

A. The CSE Case

By assuming $\theta = \varepsilon = 0$, the CSE-version of $q_M$ reduces to

$$q_{M,CS} = \sum_{k=1}^{N} \text{Re}\{\tilde{r}_k(M)\}$$

where

$$\tilde{r}_k = r_{I,k} + jr_{Q,k} = \frac{2}{\sqrt{N_0 T_s}} \int_{(k-1)T_s}^{kT_s} r(t)p(t-(k-1)T_s) e^{-j2\pi f_0 t} dt$$

is the epoch-synchronous version of the matched-filter output complex envelope.

B. The NCSE Case

Letting $\varepsilon = 0$, the NCSE-version of $q_M$ reduces to

$$q_{M,\text{NS}} = \ln I_0[\frac{1}{M!} \left(\frac{7\pi}{2}\right)^{M^2}] \sum_{k=1}^{N} |\tilde{r}_k(M)|$$

where $I_0(\cdot)$ is the modified Bessel function of order zero. By use of the approximation$^3$ $\ln I_0(x) \approx x(x > 1)$, an NCSE-version of $q_M$ is given by

$$q_{M,\text{NS}} = \sum_{k=1}^{N} |\tilde{r}_k(M)|$$

The qLLR BPSK/QPSK classification rule developed in [5] is seen to be a special case of the general $q_{M,\text{NS}}$ rule in (22), namely for $M = 2$.

$^3$Note that the argument of the Bessel function in (21) is large, corresponding to the post-detection or decision SNR, i.e., after the $N$ observed symbols have been accumulated. This is different from the pre-detection or input SNR $\eta$ of (2), which can be assumed small in noisy environments.
C. The NCAE Case

When both $\theta_c$ and $\varepsilon$ are modeled as uniformly distributed r.v.'s, the NCAE-version of $q_M$ becomes

$$ q_{M,na} = \ln \int_0^1 I_0\left(\frac{2}{M!} \left(\sum_{k=1}^N (\hat{\tau}_k)\right)^M\right) d\varepsilon $$

Equation (23) cannot be easily simplified. However, extensive simulation has shown that the test (23) and the approximated NCAE statistic $\hat{q}_{M,na}$ below (see (24)) perform quite closely:

$$ \hat{q}_{M,na} = \sum_{i=0}^{L-1} \left( \sum_{k=1}^N (\hat{\tau}_k(i))M \right) $$

In the numerical section VI, (24) will be used for this environment.

IV. Performance Analysis and Implementation of the $q_M$ Rules

We now proceed in this section to analyze the performance of the previous rules and present some implementation methods. The Correct Classification Probability (CCP) of classifying between MPSK and M'PSK by a certain rule is defined as

$$ CCP = \frac{Pr(MPSK | MPSK) + Pr(M'PSK | M'PSK)}{2} $$

In Section IV.A, the CCP corresponding to the $q_{M,cs}$ rule and the $q_{M,na}$ rule defined in (19) and (22) are analyzed. For the $q_{M,na}$ rule of (24) only the procedure will be outlined, because the derivation of its CCP is cumbersome; however, simulation results will be shown in Section VI. In Section IV.B, recursive structures for the implementation of such MPSK classifiers will be derived and discussed.

A. Performance Analysis

All deterministic decision rules of the type (6) involve a comparison of the developed statistic to appropriate thresholds. Let $T_{cs}(M)$ and $T_{ns}(M)$ be the corresponding optimal thresholds for statistics (19) and (22), respectively. We now proceed to derive their values and the corresponding CCP.

If we define, from (20), the real and imaginary components

$$ \begin{cases} A_{M,k} = \text{Re}\{(\hat{\tau}_k)^M\} \\ B_{M,k} = \text{Im}\{(\hat{\tau}_k)^M\} \end{cases} $$

then the statistics $q_{M,cs}$ and $q_{M,ns}$ are equivalent to

$$ q_{M,cs} = \sum_{k=1}^N A_{M,k} $$

and

$$ q_{M,ns} = \left[\left(\sum_{k=1}^N A_{M,k}\right)^2 + \left(\sum_{k=1}^N B_{M,k}\right)^2\right]^{1/2} $$

When $N$ is large, by virtue of a central-limit-type argument, $\sum_{k=1}^N A_{M,k}$ and $\sum_{k=1}^N B_{M,k}$ can be assumed to be approximately jointly Gaussian r.v.; this assumption has been shown numerically to be quite accurate (see simulation results of Section VI). Thus, in an approximate sense, $q_{M,cs}$ is a Gaussian r.v., whereas $q_{M,ns}$ follows a Rician or a Rayleigh distribution, depending on the presence or absence of a mean value.

As derived in Appendix A,

$$ E\left\{A_{M,k}\right\} = \begin{cases} (2\gamma_s)^{M/2}, & \text{for an MPSK input signal} \\ 0, & \text{for an M'PSK input signal with } M' > M \end{cases} $$

$$ E\left\{B_{M,k}\right\} = 0 \quad \text{(for all MPSK input signals)} $$

Here we have assumed $\theta_c = 0$ without loss of generality in the NCSE case, because the statistic $q_{M,na}$ does not depend on $\theta_c$. Also, at low SNR, the variance of the two terms in (26) can be approximated by

$$ \text{Var}[A_{M,k}] = \text{Var}[B_{M,k}] \cong (2\gamma_s)^{M/2}V_M $$

for both CSE and NCSE cases, where

$$ V_M = \sum_{l=0}^M \frac{(M)!^2}{l!(M-l)!^2} \cdot \gamma_s^{-l} $$

Since the statistic $q_{M,cs}$ is approximately a Gaussian r.v. with the same variance under both MPSK and M'PSK hypotheses, it is easy to show that the optimum threshold is given by (see eq.(29))

$$ T_{cs}(M) = \frac{1}{2} \{E[q_{M,cs} | MPSK] + E[q_{M,cs} | M'PSK]\} $$

$$ \cong \frac{N}{2}(2\gamma_s)^{M/2} $$

Thus, based on the first two moments of $A_{M,k}$, the CCP of the $q_{M,cs}$ rule can be approximated by

$$ P_{cs} \approx 1 - Q\left(\frac{N}{4V_M}\right) $$

where $Q(\cdot)$ is the Gaussian-tail integral Q-function.

For the NCSE case, we define $f_{MPSK}(q)$ and $f_{M'PSK}(q)$ to be the pdf's of the statistic $q_{M,ns}$ under either hypothesis. Using the results in (28) - (32), it is found that the former pdf is approximately a Rician

$$ f_{MPSK}(q) = \frac{(2\gamma_s)^{-M/2}}{NV_M} \exp\left[-\frac{N^2 - (2\gamma_s)^{-M/2}}{2NV_M}\right] $$

whereas the latter is approximately a Rayleigh pdf

$$ f_{M'PSK}(q) = \frac{(2\gamma_s)^{-M/2}}{NV_M} \exp\left[-\frac{(2\gamma_s)^{-M/2}}{2NV_M}\right] $$
Since both pdf's are unimodal, the optimum threshold \( T_{ns}(M) \) can be derived from the equation \( I_{MPSK}(T_{ns}(M)) = I_{MPM}(T_{ns}(M)) \) to be

\[
T_{ns}(M) \cong (2\gamma_1)^{M/2} V_M(2\gamma_1^{-1}[\exp(-N/V_M)]) \tag{37}
\]

where \( I^{-1}_0(x) \) is the inverse function of \( I_0(x) \) defined for \( x \geq 0 \). In the region of sufficiently large \( N \) where \( I_0(x) \approx e^x \) is an adequate approximation, (37) can be further simplified to

\[
T_{ns}(M) \cong \frac{N}{2} (2\gamma_1)^{M/2} \tag{38}
\]

Note that \( T_{ns}(M) \) is roughly the same as \( T_{cs}(M) \) of (33) for large \( N \). Based on the Rician/Rayleigh approximation, the CCP of the \( q_{M,na} \) rule becomes

\[
P_{ca} \cong 1 - Q\left(\sqrt{\frac{N-M}{2M!}}\right) \tag{41}
\]

and

\[
P_{na} \cong \frac{1}{2} \left[1 - \exp\left(-\frac{N}{8V_M}\right) + Q\left(\sqrt{\frac{N}{V_M}}, \sqrt{\frac{N}{4V_M}}\right)\right] \tag{39}
\]

where \( Q(\cdot, \cdot) \) is the Marcum's \( Q \)-function [11]

\[
Q(a, b) \triangleq \int_b^\infty x I_0(ax) \exp\left(-x^2 + a^2\right) dx \tag{40}
\]

At low SNR, based on the approximation \( V_M \cong \frac{M}{2\gamma_2} \) (see (32)), the CCP expressions can be approximated by

\[
P_{ca} \cong 1 - Q\left(\sqrt{\frac{N-M}{2M!}}\right) \tag{41}
\]

and

\[
P_{na} \cong \frac{1}{2} \left[1 - \exp\left(-\frac{N}{4M}\right) + Q\left(\sqrt{\frac{2N\gamma_2}{4M}}, \sqrt{\frac{N\gamma_2}{2M}}\right)\right] \tag{42}
\]

We note from (41), (42), that performance depends only on the product \( N\gamma_2^M \). Thus, to attain a pre-specified performance level, \( N \) must vary inversely proportional to \( \gamma_2^M \). The implication is that, as \( M \) increases, performance becomes more sensitive to the operating symbol SNR and a much larger \( N \) will be required to compensate any SNR loss.

Finally, let us address the issue of symbol asynchronism. A similar development that led to eq.(28) for the synchronous case can be used to show that the statistic \( q_{M,na} \) of (24) is equivalent to

\[
q_{M,na} = \sum_{i=0}^{L} \left(\sum_{k=1}^{N} A_{M,k,i}^2 + \sum_{k=1}^{N} B_{M,k,i}^2\right)^{1/2}
\]

\[
\Delta = \sum_{i=0}^{L} q_i \tag{43}
\]

where now the r.v.'s \( A_{M,k,i} \) and \( B_{M,k,i} \) are defined as

\[
A_{M,k,i} = \Re\{\mathcal{F}_k(\frac{1}{2})\}^M; \quad B_{M,k,i} = \Im\{\mathcal{F}_k(\frac{1}{2})\}^M \tag{44}
\]

For large \( N \), the \( q_i \)'s in (43) can be modeled as correlated Rician or Rayleigh r.v.'s, with the statistic \( q_{M,na} \) being the sum of such r.v.'s. The pdf of the statistic \( q_{M,na} \) under either hypothesis can be obtained following a method described in [13], but the result is too cumbersome to be included here. In any case, after these pdf's have been obtained, the optimum threshold and CCP can be derived by the same method as previously used for the \( q_{M,na} \) rule. We found that direct simulation is a shorter path for this part of the problem.

### B. Implementation

Suppose that, instead of the binary hypothesis testing problem stated so far, we are really interested in a multi-hypothesis testing problem, with \( H_i \) corresponding to \( M = 2^i \); \( i = 1, 2, \ldots, G \). Suppose further that, in the absence of any information about the prior probabilities of these hypotheses, our criterion is the Maximum Likelihood one mentioned previously. Because of the UMP nature of the qLLR test mentioned previously, the search for the largest is precisely equivalent to a sequential test\(^4\), namely the following: first, employ test \( q_1 \) to assess whether hypothesis \( M=2 \) is more likely than the \( M=4 \) one. If it is, then it will also be more likely than any other \( M > 4 \); thus, it can be declared as the final decision with no further processing. If it is not and \( M=4 \) temporarily wins, we need to repeat the question for \( M=8 \) versus \( M=8 \), etc.

In addition to this argument, a careful examination of \( A_{M,k} \) and \( B_{M,k} \) of (28) shows that they can be computed recursively in order \( M \) and time \( (k) \), as follows:

\[
A_{M,k} = A_{M/2,k}^2 - B_{M/2,k}^2; \quad A_{1,k} = r_{1,k} \tag{45}
\]

\[
B_{M,k} = 2A_{M/2,k} \cdot B_{M/2,k}; \quad B_{1,k} = r_{Q,k}
\]

with \( r_{1,k} \) and \( r_{Q,k} \) as the quadrature components defined in (20). Therefore, \( \log_2 M \) iterations are required to compute the values of \( A_{M,k} \) and \( B_{M,k} \) for each fixed \( k \).

Combining the \( q_{M,na} \) rule of (28) and the above recursions, an MPSK classifier can be constructed which identifies recursively the received waveform as one of the MPSK candidates. This multi-hypothesis sequential procedure can be implemented as shown in Fig.1. In particular, a lattice-type array consisting of a series of \( P \)-processors evaluates \( A_{M,k} \) and \( B_{M,k} \). The following decision rule of (28) and the above recursions can be computed recursively in order \( M \) and time \( (k) \), as follows:

\[
A_{M,k} = A_{M/2,k}^2 - B_{M/2,k}^2; \quad A_{1,k} = r_{1,k} \tag{45}
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\]

\[
A_{M,k} = A_{M/2,k}^2 - B_{M/2,k}^2; \quad A_{1,k} = r_{1,k} \tag{45}
\]

\[
B_{M,k} = 2A_{M/2,k} \cdot B_{M/2,k}; \quad B_{1,k} = r_{Q,k}
\]

This equivalence is not true in the general case, where a G-ary multi-hypothesis test involves (G -1) comparisons.
that all Q-processors compute the values of $q_{M,cs}$ according to (77).

V. OTHER MPSK CLASSIFIERS DERIVED FROM PM RULES

As mentioned in the introduction, other MPSK classifiers also exist besides the LF-based ones. Most of them are based on the manipulation of the MPSK phase estimates. It is instructive to show that those MPSK classifiers are, in fact, simplified versions of the LF-based classifiers. We will demonstrate that relation in this section and thus substantiate the claim that the decision-theoretic approach can provide a general inference framework for this problem. Furthermore, it will be seen that simplifying the qLLR rule towards deriving the other classifiers does not necessarily reduce implementational complexity; in fact, in certain cases, the opposite is true.

Starting from the polar representation of the received complex envelope, $\tilde{T}_k = |\tilde{T}_k|e^{j\phi_k}$, the CSE $q_{M,cs}$ statistic can be rewritten as

$$q_{M,cs} = \sum_{k=1}^{N} |\tilde{T}_k|^M \cos(M\phi_k)$$  

(46)

If one argues, on intuitive grounds, that most of the information about the phase modulation is embedded in the maximum-likelihood phase estimate

$$\hat{\phi}_{k,ML} = \tan^{-1}(r_{q,k}/r_{j,k}) = \phi_k$$  

(47)

then, dropping the amplitude terms in (46) creates a new statistic:

$$C_{coh} = \sum_{k=1}^{N} \cos(M\phi_k)$$  

(48)

Using a similar argument for the noncoherent environment, it follows that a useful statistic must be based on phase-difference estimates, $\Delta\phi_{k,j} = \phi_k - \phi_j$, for $1 \leq k,j \leq N$, so that the effect of the unknown carrier phase is removed. Now, the NCSE statistic $q_{M,ns}$ can be reformulated as

$$q_{M,ns}^2 = \sum_{k=1}^{N} \sum_{j=1}^{N} |\tilde{T}_k|^M |\tilde{T}_j|^M \cos(M\Delta\phi_{k,j})$$  

(49)

Again, dropping the amplitude terms leads to a new classifier:

$$B = \sum_{k=1}^{N} \sum_{j=1}^{N} \cos(M\Delta\phi_{k,j})$$  

(50)

This rule can be further simplified by neglecting all nonconsecutive (in time) phase difference terms:

$$C_{noncoh} = \sum_{k=1}^{N} \cos(M\Delta\phi_k)$$  

(51)

where $\Delta\phi_k \triangleq \phi_{k+1} - \phi_k$.

To explain the merit of the similar rules where $C_{coh}$ and $C_{noncoh}$ we note that, for a noiseless MPSK input, $\cos(M\phi_k) = 1$ (or $\cos(M\Delta\phi_k) = 1$) whereas $\cos(M\phi_k)$ (or $\cos(M\Delta\phi_k)$) will be a random sequence of $\pm 1$'s when $M' = 2M$, or $\pm 1$'s and 0's when $M' = 4M$, or other sets of real numbers ($\cos(\frac{2\pi i}{M'})$; $i = 1, 2, \ldots, M'$) when the input is a noiseless $M'$PSK for $M' > M$.

The above observation motivates a variant rule of the form

$$S = \sum_{k=1}^{N} \text{sgn}[\cos(M\Delta\phi_k)]$$  

(52)

with $\text{sgn}[x]$ denoting the sign function. This would be exactly equivalent to the $C_{noncoh}$ rule in a noiseless environment, but not otherwise. The $S$-classifier was first proposed by Lifdtke [1] in an ad-hoc fashion, called the Phase-Histogram Classifier (PHC). It was shown in [5] that the performance of $S$ is close to that of $C_{noncoh}$ for the BPSK/QPSK case. In fact, most performance degradation occurs when simplifying $B$ to obtain $C_{noncoh}$.

Another offspring of (48) or (51) is to use the Taylor series expansion of the $\cos(.)$ function and retain the first few terms of the series. Thus, for example,

$$C_{coh} \triangleq \sum_{k=1}^{N} \cos(M\phi_k)$$

$$= \sum_{k=1}^{N} \sum_{n=0}^{\infty} (-1)^n (M\phi_k)^{2n} / (2n)!$$

$$= N[1 + \sum_{n=1}^{\infty} (-1)^n M^{2n} / (2n)! \overline{m}_{2n}]$$  

(53)

where

$$\overline{m}_{2n} = \frac{1}{N} \sum_{k=1}^{N} (\phi_k)^{2n}$$  

(54)

is the $2n^{th}$-order sample moment of the phase estimate. This leads to families of Phase-Moments-Based Classifiers.
for any finite $L$. The rule proposed in [9], called the Statistical-Moment-Based Classifier (SMBC), is actually a special case of (55) with only the $L^{th}$ phase-moment term retained. Also related is the Phase-Based Optimal Classifier (PBOC) of [8]. Unfortunately, all such phase-based rules suffer significant performance degradation with respect to the qLLR, as reported in [9] and in the numerical section herein, making their exploration of questionable value.

For the noncoherent and asynchronous environment, in order to simplify $q_{M,n}$, we start by rewriting the epoch-synchronous version as

$$ q_{M,n} = \frac{1}{N} \sum_{k=1}^{N} \left| \sum_{n=1}^{L} (-1)^n M^{2n} \mathbb{E}[y_n^2] \right|^2 $$

where $\mathbb{E}[y_n^2]$ is the continuous-time, matched-filtered, baseband complex-envelope output as

$$ y(t) = \frac{2}{\sqrt{N_0 T_s}} \int_{t-T}^{t} r(t) p(t-t) e^{-j2\pi f_s t} dt $$

with $*$ denoting convolution. Inserting $\hat{r}(t)$ of (57) into (56) leads to

$$ q_{M,n} = \frac{1}{N} \sum_{k=1}^{N} \cos(2\pi M f_s t) [r(t)]^M |_{t=kT_s}^2 $$

where $r(t) = r(t) * (p(-t) e^{j2\pi f_s t})$ is the matched-filter output at $f_s$.

Since in the asynchronous environment the symbol timing is not known, sampling at the appropriate multiples $kT_s$ cannot take place. If we replace the summation of samples with a continuous, $NT_s$-sec integration, we arrive at

$$ Z = \int_0^{NT_s} \cos(2\pi M f_s t) [r(t)]^M dt^2 $$

We note that the Z-rule needs three stages: First, the received signal $r(t)$ is processed through a pulse-matched prefilter at passband with impulse response $p(-t) e^{j2\pi f_s t}$. The output of the prefilter is raised to the $M^{th}$ power and, at the last stage, the signal is down-converted in quadrature form to baseband (by mixing it with the frequency $f_s$) and integrated (i.e., lowpass filtered) for the desired observation length. This is precisely the $M^{th}$-law classifier mentioned previously, which has been shown here to be a slightly different version of the qLLR rule (23) for this environment. In practice, a simpler prefilter is sometimes used (see Fig. 2), such as a brick-wall passband filter of bandwidth $2/T_s$ Hz.

VI. NUMERICAL PERFORMANCE COMPARISONS

In this section, the CCP performance of the various MPSK classifiers is examined and comparisons are made, backed by extensive computer simulation. The number of the observed symbols is assumed throughout to be $N = 100$. A rectangular baseband pulse is assumed.

To start, we have performed an analytic evaluation of the $M^{th}$-law classifier; details can be found in Appendix B. It has been assumed in the analysis that the signal self-noise at the output of the prefilter is negligible, and that the filtering effect manifests itself in a power loss by the factor

$$ \epsilon = \int_{-\infty}^{\infty} \frac{\sin^2(\pi f)}{(\pi f)^2} df \approx 0.9038 $$

Its CCP is shown in Appendix B to be

$$ P_{M^{th-law}} = \frac{1}{2} \left[ 1 - \exp \left( -N \frac{\beta_M^2}{2} \right) + Q \left( \sqrt{\frac{N \beta_M^2}{2}} \right) \right] $$

where $Q(\cdot)$ is the Marcum Q-function, and

$$ U_M = \sum_{k=1}^{M} 2^{-k}(M!)^2 (\gamma_s)^{-k} G_k + 2^{M-2} M S M_{\gamma_s}^{-M} $$

when $\gamma_s \ll 1$, by use of the approximation

$$ U_M \approx 2^{M-2} M S M_{\gamma_s}^{-M} $$

It is found that

$$ P_{M^{th-law}} \approx \frac{1}{2} \left[ 1 - \exp \left( -N \beta_M^2 \right) \right] + Q \left( \sqrt{\frac{2N \beta_M^2}{M!}} \right) $$

Note that they only differ in the type of phase measured; in the latter case, (51) involves phase differences.
Since the classical $M^th$-law classifier does not exploit the symbol timing and pulse-shape information incorporated into the $q_{M,n}$ qLLR rule, it is expected that it will require more SNR than the latter in order to attain the same performance level. At low SNR, comparing (42) with (66), we note that the additional SNR required by the $M^th$-law classifier is

$$10 \log \beta^{-1} \approx 3.45 - \frac{10}{M} \log \left( \frac{2}{S_M} \right) \text{ (dB)} \quad (68)$$

This is about 1.9 dB for the BPSK-versus-QPSK case and 2.6 dB for the QPSK-versus-8PSK case. The CCP performance of $q_{M,cs}$ and $q_{M,ns}$ was compared to that of the corresponding optimal LLF rules defined by (4)-(6), and the results are shown in Figures 3(a), 3(b), and 3(c) for the BPSK/QPSK, QPSK/8PSK, and 8PSK/16PSK cases, respectively. It can be seen that the performance degradation of $q_{M,cs}$ and $q_{M,ns}$ rules versus the optimal is negligible for all SNR. The interesting conclusion here is that, although the qLLR rules were obtained under a low-SNR assumption, their performance is quite good throughout the useful SNR range. When preparing Figures 3(a)-3(c), the threshold defined in (37) is used for the $q_{M,ns}$ rule. Most likely, however, the simpler threshold of (38) would be implemented in a practical setup. Further simulation results have shown that the performance of the $q_{M,ns}$ rule

It was claimed in [9] that the qLLR rules perform well only for low SNR. This is evidently not so, as concluded not only from the numerical results of this Section but also from those of [9] itself. Apparently, the authors of [9] have confused the employment of a low-SNR argument for deriving the qLLR rules with the assessment of the actual performance (versus SNR) of these rules.
degrades by less than 0.5 dB when the latter threshold is used.

Figure 4 compares the CCP performance of five BPSK/QPSK classifiers: the $q_{2,3}$, the PBOC [8] and SMBC [9] rules, which assume known carrier phase (CSE), plus the $q_{2,n}$ and PHC rules, which assume unknown carrier phase (NCSE). The performance curves for the PBOC and the SMBC rules are directly extracted from [8, Fig. 4] and [9, Fig. 11]. Comparisons of the three coherent classifiers indicate that the PBOC rule is 1.2 dB worse than the $q_{2,3}$ rule, and that the SMBC rule is 6.1 dB worse than the $q_{2,3}$ rule at $\gamma_s = -6 dB$. From the comparisons of the noncoherent classifiers, the PHC rule is 6.8 dB worse than the $q_{2,3}$ rule at $\gamma_s = -6 dB$.

The CCP performance of the asynchronous classifiers, evaluated by simulation, where both the carrier phase and the symbol timing are assumed unknown, are examined in Figures 5(a) and 5(b) for the BPSK/QPSK and QPSK/8PSK cases. The performance of the synchronous $q_{M,n}$ rules is also shown as a benchmark. It is seen that the square-law ($2^{nd}$-law) classifier with a brick-wall prefilter is 1.7 dB worse than the $q_{2,n}$ rule at $\gamma_s = -8 dB$. Also, the $q_{M,n}$ rules with small number of discretized epoch uncertainty levels $L$ (see (24)), which is 4 or 8, perform close to the $q_{M,n}$ classifiers and better than the $M^{th}$-law classifiers.

VII. CONCLUSIONS

This paper has demonstrated that the likelihood approach provides a systematic way of harnessing classes of algorithms for the task of MPSK modulation classification. It also constructs a theoretical framework within which all currently known MPSK classifiers can be interpreted as particular suboptimal versions of the optimal LLF rules.

The proposed quasi-optimal $q_M$ rules have been shown, by analysis and simulation, to process the best performance in terms of correct classification probability among all known MPSK classifiers, and to be negligibly away from the globally optimal performance. Finally, a lattice-type structure has been proposed for the effective implementation of these rules.
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APPENDIX A

THE FIRST TWO MOMENTS OF $A_{M,k}$ AND $B_{M,k}$

According to the moment theorem for complex Gaussian processes presented in [12], the following identity regarding the expectations of a zero-mean complex Gaussian process $\hat{n}(t)$ is true:

$$E\{\hat{n}'(t)\hat{n}(t + \tau)\} = \begin{cases} k! [E\{\hat{n}'(t)\hat{n}(t + \tau)\}]^k, & k = i \neq 0 \\ 0, & k \neq i \neq 0 \end{cases}$$ (A.1)

The above can be generalized to all non-zero mean processes, $\hat{n}(t)$, by substituting $\hat{n}(t)$ for $\hat{n}(t)$ into the above identity. Let $\tau = 0$ and denote $\hat{z} = \hat{n}(0)$. Then, two useful identities for computing the moments of $A_{M,k}$ and $B_{M,k}$ are obtainable from the cases of $(k = 0, i = M)$ and $(k = i = M)$ as follows:

$$E\{\hat{z}^M\} = (E\{\hat{z}\})^M$$ (A.2)

and

$$E\{\hat{z}^{2M}\} = \sum_{i=0}^{M} \binom{M}{i}^2 E\{\hat{z}\}^{2(M-i)}$$ (A.3)

For a fixed phase $\theta_k$, the r.v. $\hat{r}_k$ defined in (20) is a complex Gaussian r.v. with mean $E\{\hat{r}_k\} = \sqrt{2\gamma} e^{j\theta_k}$ and variance $Var[\hat{r}_k] = 2$. Applying the identity (A.2), the conditional mean of $\hat{r}_k$ is

$$E\{\hat{r}_k^M | \theta_k\} = (2\gamma)^{M/2} e^{jM\theta_k}$$ (A.4)

Averaging over $\theta_k$ we arrive at the unconditional mean

$$E\{\hat{r}_k^M\} = \begin{cases} (2\gamma)^{M/2}, & \text{for an MPSK input signal} \\ 0, & \text{for an M'PSK input signal with } M' > M \end{cases}$$ (A.5)

which is (29), (30). From eqs. (26) and (45) it follows that

$$A_{M,k}^2 + B_{M,k}^2 = |\hat{r}_k|^{2M}$$ (A.6)

$$A_{M,k}^2 - B_{M,k}^2 = A_{2M,k} = Re\{E\{\hat{r}_k^{2M}\}\}$$ (A.7)

Therefore, the second moments of $A_{M,k}$ and $B_{M,k}$ can be computed from the values of $E\{\hat{r}_k^{2M}\}$ and $Re\{E\{\hat{r}_k^{2M}\}\}$ through the following identities:

$$Var[A_{M,k}] = \frac{1}{2} (E\{|\hat{r}_k^{2M}\} + Re\{E\{|\hat{r}_k^{2M}\}\}) - (E\{A_{M,k}\})^2$$ (A.8)

Furthermore, $E\{\hat{r}_k^{2M}\}$ and $Re\{E\{\hat{r}_k^{2M}\}\}$ can be computed via the identities (A.2) and (A.3) as

$$E\{\hat{r}_k^{2M}\} = \begin{cases} (2\gamma)^M, & \text{MPSK or 2MPSK input signal} \\ 0, & \text{M'PSK input signal with } M' > 2M \end{cases}$$ (A.9)

$$E\{\hat{r}_k^{2M}\} = (2\gamma)^M \cdot 2V_M$$ (A.10)

where $V_M$ is defined in (32). Accordingly, we arrive at

$$Var[A_{M,k}] = \begin{cases} (2\gamma)^M V_M, & \text{MPSK input signal} \\ (2\gamma)^M (V_M + 1), & \text{2MPSK input signal} \\ (2\gamma)^M (V_M + \frac{1}{2}), & \text{M'PSK input signal with } M' > 2M \end{cases}$$ (A.11)

$$Var[B_{M,k}] = \begin{cases} (2\gamma)^M V_M, & \text{MPSK input signal} \\ (2\gamma)^M (V_M + 1), & \text{2MPSK input signal} \\ (2\gamma)^M (V_M + \frac{1}{2}), & \text{M'PSK input signal with } M' > 2M \end{cases}$$ (A.12)

which result in (31) at low SNR.

APPENDIX B

PERFORMANCE EVALUATION OF THE $M$TH-LAW CLASSIFIER

In Fig. 2, the $M$th-law classifier is divided into three stages: a prefilter, which is a brick-wall bandpass filter with bandwidth $2/T_s$ centered at $f_c$, an $M$th-law nonlinear device and a postfilter, which is composed of I- and Q-matched filters centered at $Mf_c$. The output of the prefilter is denoted by

$$x(t) = s_f(t) + n_fBP(t) = Re\{z(t) e^{j2\pi f_c t}\}$$ (B.1)

where the filtered signal $s_f(t)$ is assumed undistorted with power attenuated by a factor $\epsilon$ (see (60)) and $n_fBP(t)$ is the bandpass Gaussian noise. The output of the $M$th-law device is given by

$$y(t) = [x(t)]^M = \frac{1}{2M} [\hat{z}(t) e^{j2\pi f_c t} + \hat{\bar{z}}(t) e^{-j2\pi f_c t}]^M$$

$$= \frac{1}{2M} \sum_{k=0}^{M-1} \binom{M}{k} [\hat{z}(t) e^{j2\pi f_c t}]^k $$ (B.2)

where only the term $\hat{z}(t)$ contributes to the power at $Mf_c$-band. The correlation function of $\hat{u}(t)$ can be decomposed in terms of the correlation functions of the filtered signal $s_f(t)$ and bandpass noise $n_fBP(t)$ as

$$R_u(\tau) = \frac{1}{2M} \sum_{k=0}^{M-1} \binom{M}{k} [\hat{z}(t) e^{j2\pi f_c t}]^k \hat{z}(t + \tau)$$ (B.3)
\[ S_y(Mf_c) = S_y(0) = \frac{1}{22M} \sum_{k=0}^{M} (M-k)^2 k! \int_{-\infty}^{\infty} R_{y(M-k)}(r) R_k(r) \, dr \] (B.4)

After expanding the filtered signal,
\[ \hat{y}_f(t)^{M-k} = (2cS)^{M-k} \sum_{n=1}^{N} \left( e^{(M-k)\theta_n} u_T(t-nT_s) + \left(1 - |E\{e^{(M-k)\theta_n}\}|^2\right) p(r) \right) \] (B.6)
with
\[ g(r) = \begin{cases} 1 - \frac{1}{T_s}, & |r| < T_s \\ 0, & |r| \geq T_s \end{cases} \] (B.7)

On the other hand, it can be shown that
\[ \int_{-\infty}^{\infty} R_k(r) g(r) \, dr = \frac{T_s}{2} \left( \frac{4N_0}{T_s} \right)^k S_k, \quad k \neq 0 \] (B.8)
\[ \int_{-\infty}^{\infty} R_k(r) g(r) \, dr = \frac{T_s}{2} \left( \frac{4N_0}{T_s} \right)^k G_k \] (B.9)

where \( S_k \) and \( G_k \) are defined in (63) and (64). Applying (B.6), (B.8) and (B.9) to (B.4), the PSD of \( y(t) \) at \( Mf_c \) is obtained as
\[ S_y(Mf_c) = (eS^2)^M |E\{e^{Mf_c}\}|^2 \delta(f - Mf_c) + T_s \left( \frac{eS^2}{2} \right)^M \]
\[ + \frac{4N_0}{T_s} \sum_{k=1}^{M} \frac{(M-k)^2}{k!^2} \left( Mf_c - k \right) |E\{e^{(M-k)\theta_n}\}|^2 S_k \]
\[ + \left( 1 - |E\{e^{(M-k)\theta_n}\}|^2 \right) p(r) \] (B.10)

where a \( \delta(f - Mf_c) \) with nonzero coefficients means a frequency tone at \( Mf_c \). Given that the input to the \( M^{th} \)-law classifier can be an MPSK or \( M' \)PSK signal with \( M' > M \), the above PSD expression simplifies to be
\[ S_y(Mf_c; M') = \left( \frac{eS^2}{2} \right)^M \delta(f - Mf_c) \]
\[ + T_s \sum_{k=1}^{M-1} \frac{(M-k)^2}{k!^2} \left( Mf_c - k \right) |E\{e^{(M-k)\theta_n}\}|^2 S_k \]
\[ + \left( 1 - |E\{e^{(M-k)\theta_n}\}|^2 \right) p(r) \] (B.11)

Thus, a spectral line can be found at \( Mf_c \) for a given an MPSK signal, and no spectral line exists for an \( M' \)PSK signal.

Based on the above PSD expressions and assuming \( N \gg 1 \), \( y_T \) and \( y_Q \) in Figure 2 are approximately independent Gaussian r.v.'s with moments
\[ (E\{y_T\})^2 + (E\{y_Q\})^2 = \left( \frac{eS}{2} \right)^2 \left( M(T_s)^2 \right) \]
\[ 0 \quad (M'PSK) \]
\[ Var(y_T) = Var(y_Q) = \frac{NT_s}{2} \cdot S_y(Mf_c) \] (random part)
(B.13)
(B.14)

The pdf of \( z \) at the output of the postfilter, normalized by the factor \( \frac{1}{\sqrt{T_s}} \), is therefore
\[ f_z(z) = \frac{1}{2NU_M} \exp\left( - \frac{N^2 + z}{2NU_M} \right) \] (MPSK)
\[ f_z(z) = \frac{1}{N(2U_M + 1)} \exp\left( - \frac{N^2 + z}{N(2U_M + 1)} \right) \] (M'PSK)
where
\[ U_M = \sum_{k=1}^{M} \frac{2^{k-2}(M-k)!(\psi_k)^{-1}}{k![(M-k)!!]^2} \]
\[ + 2^{M-2} M! S_M (\psi_M)^{-M} \] (B.17)

When \( N \gg 1 \), the optimal threshold has the form
\[ T_i = U_M^2 \] (B.18)
and the CCP is expressed in (61).

REFERENCES


Chung-Yu Huang received the B.Sc. degree in electrical engineering from National Taiwan University, Taipei, Taiwan, in 1984 and the Ph.D. degree in electrical engineering from University of Southern California, Los Angeles, California, in 1991.

During 1991 - 1993, he was a Member of Technical Staff at COMSAT Labs, Maryland, where he had worked on INMARSAT-C terminal design, video compression for satellite broadcasting system, and facsimile signal compression for mobile satellite communication.

Since May 1993, he is with LINKCOM Inc., Hsinchu, Taiwan, as a technical manager. He is currently leading a technical team, working on low-bit-rate voice compression and implementation of telephone subsystem for a satellite terminal network (VSAT) system.

Andreas Polydoros (M'78, SM'92, F'95) was born in Athens, Greece, in 1954. He was educated at the National Technical University of Athens, Greece (Diploma in EE, 1977), State University of New York at Buffalo (MSEE, 1977) and the University of Southern California (Ph.D., EE, 1982). He has been a faculty member in the Electrical Engineering/System Department and the Communication Sciences Institute (CSI) at USC since 1982, promoted to Professor in 1992.

His general area of scientific interest is statistical communication theory with applications to spread-spectrum systems, signal detection and classification, and multi-user radio networks. He has over a dozen of years of teaching, research and extensive consulting experience on these topics, both for the government and industry.

Professor Polydoros is the recipient of a 1986 NSF Presidential Young Investigator Award. He was the Associate Editor for Communications of the IEEE Trans. Infor. Theory (1987 - 1988), and the Guest Editor of the July 1993 Special Issue on “Digital Signal Processing in Communications” for Digital Signal Processing: A Review Journal.