CLASSIFICATION OF MODULATION MODES USING TIME-FREQUENCY METHODS

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ABSTRACT

This paper proposes a new technique for feature extraction of modulated signals which is based on a pattern recognition approach. The new algorithm uses the cross Margenau-Hill distribution, autoregressive modeling, and amplitude variations to detect phase shifts, frequency shifts, and amplitude shifts, respectively. Our method is capable of classifying PSK2, PSK4, PSK8, PSK16, FSK2, FSK4, QAM8 and OOK signals. Unlike most of the existing decision-theoretic approaches, no explicit a priori information is required by our algorithm. Consequently, the method is suitable for application in a general non-cooperative environment. Furthermore, our approach is computationally inexpensive. Simulation results on both synthetic and "real world" short-wave signals show that our approach is robust against noise up to a signal-to-noise ratio (SNR) of approximately 10 dB. A success rate greater than 94 percent is obtained.

1. INTRODUCTION

Modulation classification of digital signals has been of interest for more than 20 years. In short-wave communication, there is a need to classify the modulation mode of an incoming signal before demodulation is done. Basic modulation classification systems include three subsystems, namely the preprocessing subsystem, the feature extraction subsystem, and the classification subsystem. In the preprocessing subsystem, the signal is translated to the baseband and filtered. The feature extraction subsystem (see Fig. 1) maps the signal into a feature vector that is used by the classification subsystem (see Fig. 2) to assign the signal to a specific modulation class. Pattern recognition and decision-theoretic methods for modulation classification can be found in the literature.

In 1969, Weaver et al. [1] used the signal's spectral content and a nearest neighborhood classifier. Liedtke [2], Jondral [3], and many subsequent approaches introduced the instantaneous frequency and the phase histogram into their feature vector. In 1988, Polydoros and Kim [4, 5] proposed the use of likelihood functionals for a symbol-synchronous classifier and, in 1990, statistical moments of the signal phase were used. In 1992, Reichert [6] proposed a modulation classifier based on higher order statistics. In 1994, the wavelet packet transform was used by Ta [7], and the continuous wavelet transform was used by Lin and Kuo [8, 9] and Ho [10] as the first representatives of time-frequency methods.

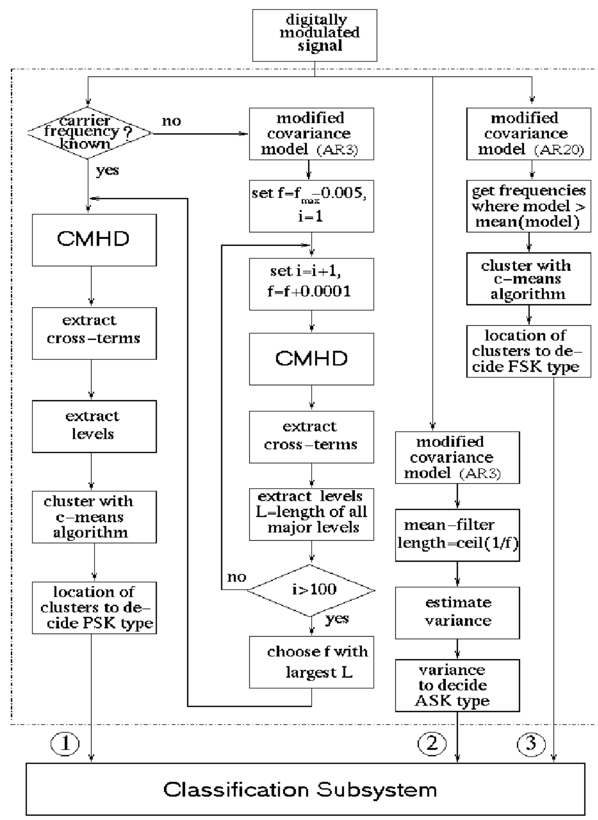


Figure 1: Overview of the feature extraction subsystem.

2. CROSS MARGENAU-HILL DISTRIBUTION

To extract information about the amplitude, frequency, and phase from a digitally modulated signal, we must represent the signal not only with its magnitude but also with its phase information. The Margenau-Hill (time-frequency) distribution (MHD), a member of Cohen's fixed kernel class, is known to preserve phase information. The cross MHD is defined by [11]

$$CMHD_{x,y}(t,f)=\frac{1}{2}\int_{-\infty}^{\infty}\left[x(t+\tau)y^{*}(t)+x(t)y^{*}(t-\tau)\right]e^{-j2\pi f\tau}d\tau\,. \quad (1)$$

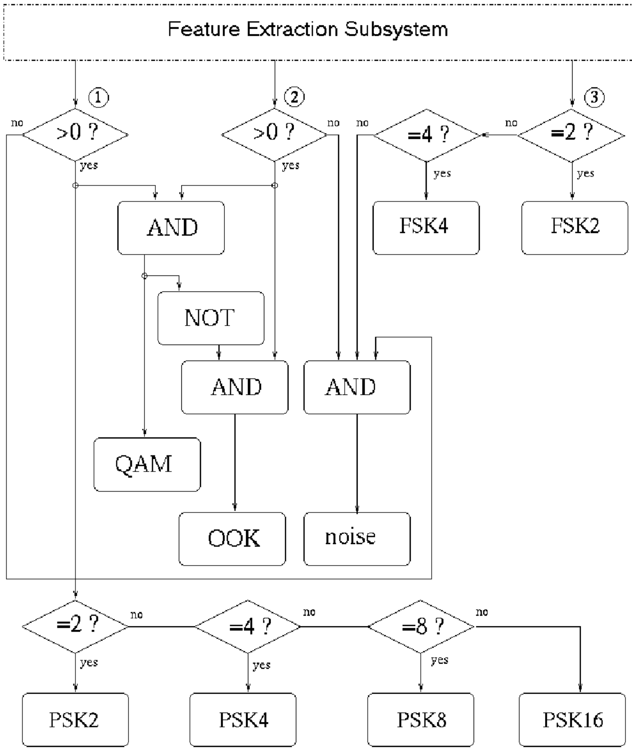


Figure 2: Overview of the classification subsystem.

We set $y(t) = e^{j2\pi f_c \tau}$, where f_c denotes the carrier frequency of the signal under analysis. If the carrier frequency is not known a priori, it can be estimated in two steps as described in Section 2.2. The CMHD expression in Eq. (1) simplifies to

$$\begin{aligned} CMHD_x(t,f) &= \frac{1}{2}\int_{-\infty}^{\infty}\left[x(t+\tau)e^{-j2\pi f_c t} + x(t)e^{-j2\pi f_c (t-\tau)}\right]e^{-j2\pi f\tau}d\tau \\ &= \frac{1}{2}\int_{-\infty}^{\infty}\left\{\left[x(t+\tau)+x(t)e^{j2\pi f_c \tau}\right]e^{-j2\pi f_c t}\right\}e^{-j2\pi f\tau}d\tau \end{aligned} \quad (2)$$

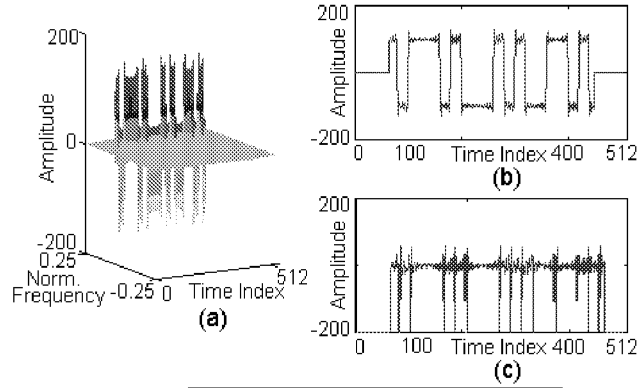
and a straightforward discretization of Eq. (2), which is needed for computation, leads to alias-free results for signals sampled at or above the Nyquist rate provided the analytic signal is used. This is described in [12].

2.1 FEATURES OF THE CROSS MARGENAU-HILL DISTRIBUTION

The CMHD, as given by Eq. (2), shows terms that are related to phase shifts of the signal under analysis in a row along time that is located at the carrier frequency. This row is extracted from the CMHD as shown in Fig. 3. Because the resulting function of time, $q(t)$, defined by

$$q(t) = \left|CMHD(t, f = f_c)\right|, \quad (3)$$

contains our phase parameter, we name it the "feature function of the CMHD" or simply the "feature function". For M-ary PSK signals, specific levels are present in the feature function $q(t)$. Fig. 3(d) depicts the number of and the relative level amplitudes for PSK2, PSK4, PSK8 and PSK16 signals.



	level 1	level 2	level 3	level 4
PSK2	**100**			
PSK4	**100**	**0**		
PSK8	**100**	**74**	**0**	
PSK16	**100**	**74**	**40**	**0**

(d)

Figure 3: (a) CMHD, (b) one column along time of the CMHD, and (c) feature function of a PSK2 signal. (d) Relative amplitude levels in the feature function for PSK2, PSK4, PSK8 and PSK16 signals.

2.2 CARRIER FREQUENCY ESTIMATION

If the carrier frequency, f_c, is not known, we estimate it as follows. First, an approximation is obtained by modeling the signal under analysis via an autoregressive modified covariance model of order 3 and looking for the frequency with the highest peak in the resulting power spectral density (PSD). This frequency estimate is found to be more accurate than that provided by a fast Fourier transform (FFT) based estimation because phase shifts in the signal correspond to changes in the instantaneous frequency [8].

In the second step, the following iterative process is done for several closely spaced frequencies, f_i, leading to the correct carrier frequency, f_c. From the CMHD, the feature function $q(t)$ can be extracted for each frequency f_i as described in Section 2.1 and shown in Fig. 3. For the correct frequency, constant levels show up in $q(t)$. If the frequency is chosen inaccurately, a sinusoidal component is superimposed.

2.3 CLASSIFICATION OF M-ARY PSK MODULATION TYPES

Low values of the feature function's gradient indicate the presence of constant levels. Hence, all samples in $q(t)$ corresponding to a gradient smaller than a threshold are marked. We have found that $^1/_{15}$ of the maximum value of the gradient performs well as the threshold. The mean of $q(t)$ is calculated for each interval of marked samples that is longer than $3\cdot\text{round}(\log_2(N)-7)$ samples, where N is the number of samples in the signal. By applying the c-means algorithm, the cluster centers C_1, C_2, ..., and C_5, sorted in ascending order, are obtained. Then, a fuzzy logic classifier decides how many different cluster centers are found by the c-means algorithm.

3. AUTOREGRESSIVE MODIFIED COVARIANCE MODELING

By modeling frequency-shift keying (FSK) signals with an autoregressive modified covariance model, the power spectral density (PSD) can be observed. Our approach uses spectral peaks in the PSD to determine the number of frequencies in the signal. To be able to distinguish noise from FSK modulation types, the order of the AR model is chosen high. Further, a high model order helps in resolving closely spaced frequency components. Simulations show that a model order of 20 works well.

By applying a smoothing filter in the time domain whose length is larger than one period of the signal, the envelope of the signal's amplitude is obtained. The variance of the envelope, σ^2, is a parameter which monitors amplitude changes in the signal. In our approach, the smoothing filter maps each sample to the mean of the magnitude of all samples in a rectangular window of length L. The length of the window, L, matches the carrier period. This length is approximated as the reciprocal value of the peak frequency, f_c, of an autoregressive modified covariance model. Simulations show that order 3 is sufficient for approximating the carrier period of ASK and QAM signals.

3.1 CLASSIFICATION OF M-ARY FSK MODULATION TYPES

We use the mean of the PSD as a threshold to decide on a spectral component present in the signal. All frequencies with a PSD higher than the mean of the PSD are clustered into 4 centers, C_1, C_2, C_3, C_4, using the c-means algorithm. The following distances are then computed:

$$d_1=C_2-C_1, \qquad d_2=C_3-C_2, \qquad d_3=C_4-C_3. \tag{4}$$

From these distances, two parameters can be derived as

$$d_{max}=\max(d_1,d_2,d_3), \qquad t=0.6\cdot d_{max}. \tag{5}$$

The locations of these four cluster centers are used to decide if a FSK modulation type is present in the signal. In order to qualify for a FSK modulation type, the cluster centers have to maintain the constraints given in Table 1 where $\vee$ denotes logical OR and $\wedge$ denotes logical AND.

	FSK2	FSK4
Constraint 1	$d_1>t \vee d_2>t \vee d_3>t$	$(d_1>t \wedge d_2>t) \vee (d_1>t \wedge d_3>t) \vee (d_2>t \wedge d_3>t)$
Constraint 2	$d_{max}>C_1$	$d_{max}>C_1$

Table 1: Distance constraints for spectral peaks in FSK signals.

3.2 CLASSIFICATION OF ASK AND QAM MODULATION TYPES

To decide whether the amplitude of a signal under analysis is modulated or not, the variance of the envelope is checked to see if it exceeds a threshold. The decision making about the amplitude information, $\hat{a}$, is implemented by

$$\hat{a}=\begin{cases}1 & , if\ \sigma^2>1.8 \\ 0 & , otherwise\end{cases}. \tag{6}$$

4. SIMULATIONS

For a signal-to-noise ratio (SNR) of 15 dB, the feature functions of synthetic 512-point PSK2, PSK4, PSK8 and PSK16 signals are depicted in Fig. 4(a)-(d), respectively. The presence of constant levels in the feature function, located as shown in Fig. 3(d), can clearly be observed.

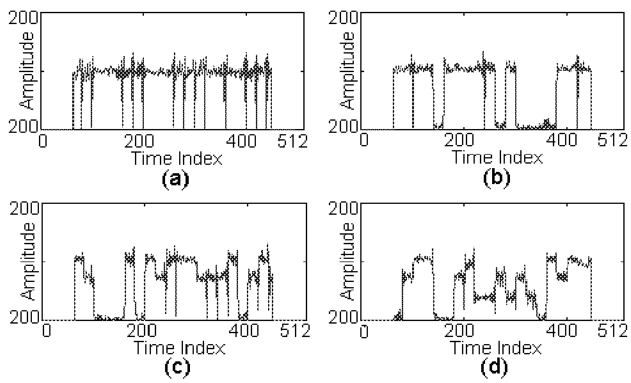


Figure 4: Feature function of a (a) PSK2, (b) PSK4, (c) PSK8 and (d) PSK16 signal with a signal-to-noise ratio of 15 dB.

By using signals that contain the same symbols with a SNR of 10 dB or "real world" short-wave signals, the feature function shows correctly located, distinctive constant levels as illustrated in Fig. 5 and Fig. 6. Accordingly, the error classification rate (ECR) is low.

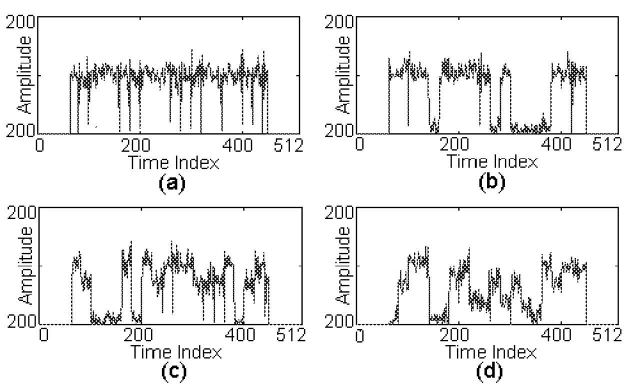


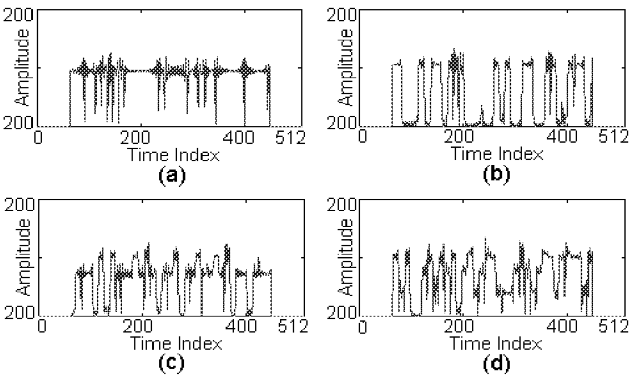
Figure 5: Feature function of a (a) PSK2, (b) PSK4, (c) PSK8 and (d) PSK16 signal with a signal-to-noise ratio of 10 dB.

The PSD of a FSK2 and a FSK4 signal, estimated by the modified covariance approach, is depicted in Fig. 7(a)-(b). Fig. 8(b) illustrates the envelope of the OOK signal depicted in Fig. 8(a). The two different levels of the amplitude can be perceived.

The ECR - performing 500 simulations - with synthetic PSK2, PSK4, PSK8, PSK16, FSK2, FSK4 and QAM8 signals with a SNR of 10 dB are shown in Table 2. Table 3 refers to the ECR for "real world" short-wave signals.

5. CONCLUSION

We demonstrated that the cross Margenau-Hill distribution is a powerful tool for extracting the phase information from a signal. For the estimation of the carrier frequency, the CMHD can be used. Frequency and amplitude information can be obtained by modeling a signal with an autoregressive model of high order and checking for the number of peaks in the model. All feature extraction methods are computationally simple. The proposed implementation clearly outperforms classical methods for modulation recognition. The classification subsystem is implemented in a straightforward manner by using a decision tree. No explicit a priory information is used by our modulation classifier.



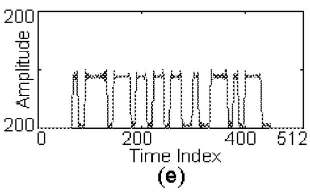


Figure 6: Feature function of a "real world" short-wave (a) PSK2, (b) PSK4, (c) PSK8, (d) PSK16 and (e) QAM8 signal.

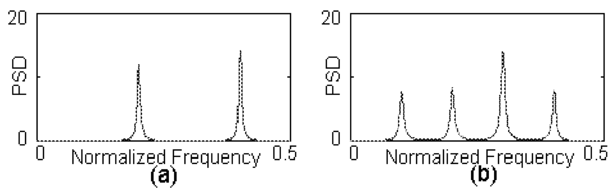


Figure 7: Power spectral density using the modified covariance model of order 20 of a (a) FSK2 and (b) FSK4 signal.

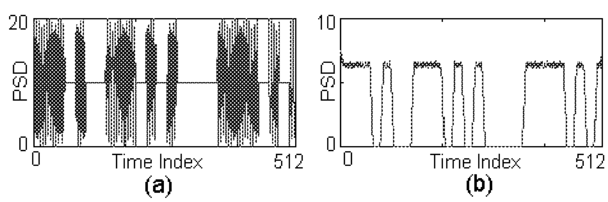


Figure 8: (a) OOK signal and (b) envelope of the OOK signal.

	with 10 dB SNR classified to								
	OOK	FSK2	FSK4	PSK2	PSK4	PSK8	PSK16	QAM8	noise
OOK	**98**								**2**
FSK2		**99**	**1**						
FSK4		**2**	**98**						
PSK2				**98**					**2**
PSK4				**1**	**98**				**1**
PSK8					**3**	**96**			**1**
PSK16						**1**	**99**		
QAM8	**1**				**2**			**97**	
noise	**1**					**2**	**3**		**94**

Table2: Error classification rate for synthetic signals with a SNR of 10 dB.

	classified to								
	OOK	FSK2	FSK4	PSK2	PSK4	PSK8	PSK16	QAM8	noise
OOK	**98**								**2**
FSK2		**99**							**1**
FSK4		**2**	**98**						
PSK2				**99**			**1**		
PSK4				**1**	**98**	**1**			
PSK8					**1**	**97**	**2**		
PSK16					**1**	**1**	**98**		
QAM8					**1**			**99**	

Table 3: Error classification rate for real world short-wave signals.

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