MODULATION IDENTIFICATION USING NEURAL NETWORKS FOR COGNITIVE RADIOS

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ABSTRACT

This paper presents a signal modulation classifier design using artificial neural networks. We analyze system-level issues including carrier synchronization, bandwidth estimation, and modulation classification. This is an extension of previous work with the addition of standard-free signal classification as well as an in-depth analysis of the feature space used in the neural network. The results show promising classification statistics with over 80% success rates in the presence of noise even with higher-order digital modulations.

1. INTRODUCTION

Cognitive radios (CR) are intelligent communications devices that use knowledge of the external environment and user needs to reconfigure themselves to optimize quality of service (QoS). Work on creating these radios has focused on adaptation on the physical (PHY) and medium access control (MAC) layers, which allow waveform adaptation to improve QoS as well as better management of wireless resources like spectrum [1].

Knowledge of the external environment is generally comprised of information extracted from the propagation channel modeling and the identification of other signals present on the channel. In the presence of additional radios, signal identification will provide the CR with the tools to either communicate with or avoid them. For this to be a feasible implementation, a cognitive radio requires an efficient signal classification system. Signal classification is the focus of this paper, which extends previous work in this area for application to cognitive radios.

Signal recognition is a systematic design challenge which requires hierarchical signal processing from radio frequency (RF) to baseband in order to obtain comprehensive knowledge from the carrier to the information bit stream. Unlike conventional radios, the CR approach requires the receiver to be aware of its radio environment. The challenge is in the design of a universal receiver that can recognize various modulated waveforms with distinct properties.

A major issue in conventional receiver design is synchronization, specifically carrier recovery and symbol timing if digital modulation is used. In modern commercial applications, power- and bandwidth-efficient modulation schemes make synchronization difficult [2]. Besides carrier recovery, symbol timing is essential for coherent demodulation. Although there are various symbol synchronization and timing algorithms in literature [3], most of them rely on prior knowledge of a given standard; information like symbol rate, filter characteristics, and modulation.

Since the CR approach does not assume that such key information is available, a standards-free method is required to extract these waveform features. Such a "cognitive" receiver must be able to synchronize to various signals and recognize their modulation to establish a link in the PHY layer.

The modulation classifier can be implemented at a digitized intermediate frequency (IF) by using temporal statistical analysis [4] when signal-to-noise ratio (SNR) is moderate or high or using spectral analysis when SNR is low [5]. It can also work with a digital baseband synchronizer like a vector-phase analyzer with a moderate SNR [6]. However, most previous work on modulation classification has assumed knowledge of the carrier frequency, the symbol rate, or the availability of infinite computational power [7], all of which are usually unavailable in any practical implementation.

A systematic understanding of synchronization for a cognitive radio receiver implementation is presented in Section 2. Section 3 analyzes different approaches to modulation classification. Section 4 proposes and explains a neural network for modulation classification, and Section 5 provides performance evaluation through simulation.

2. SYNCHRONIZATION FOR COGNITIVE RADIO

2.1 Signal detection and carrier recovery at RF

The RF signal is typically detected by energy correlation in analog circuitry and then downconverted to IF or baseband for further processing. For the standards-free approach of cognitive radios, the local oscillator (LO) should scan the complete target band in search of signals, and a signal carrier should be recovered without specific modulation knowledge. Although this seems impossible, there are some general implementation practices we can make use of.

First, pilot signals are popular in commercial standards, especially for broadcasting and multiple access systems. Pilot signals typically are pure tones or have very distinct information patterns which are easy to capture by a sweeping LO. By recognizing the information in the pilot tone, the receiver may identify the signal standard.

Second, when a pilot signal is not available, pure ad-hoc carrier recovery is needed. Fortunately, most narrow band signals fall into two groups. One is with strong carrier and the other is with suppressed carrier but a symmetric spectrum. For the first case, a conventional narrow-bandwidth phase-lock loop (PLL) can recover the carrier; for the second case, a second-order nonlinear operation can remove the modulation and produce a frequency component at double the carrier frequency [8].

The recovered carrier is a coarse estimation of the true carrier but close enough to initialize the PLL to achieve carrier synchronization. The RF signal is then downconverted to IF and digitized for a second downconversion to baseband where accurate IF carrier synchronization is obtained through digital signal processing (DSP). This process is explained in the next section. Both carrier recovery with and without prior signal knowledge can improve performance by applying a feedback loop from the baseband demodulator (or phase estimator) for fine tuning [3]. The blind signal carrier estimation in a CR receiver may have a larger offset which necessitates feedback information from baseband DSP. PLL loop gain can also be controlled according to feedback. The loop gain adjusts the trade-off between sensitivity and speed [9], which allows the PLL to acquire unknown signals.

2.2 Synchronization at digital IF and channel bandwidth estimation

In a CR receiver, unlike the conventional standard-specific case, the waveform recognition is ad-hoc and many key features need to be extracted from the signal instead of being known in advance. Most of these, including IF carrier frequency, symbol rate, pulse shape, and modulation, are waveform-related, so they have to be extracted at the digital IF stage with a high sampling ratio. The digital carrier synchronization can work under a small residual frequency offset and phase noise introduced by the preceding analog PLL. Both analog and digital PLLs can be aided by decision feedback from baseband and thus work jointly on a global synchronization [3]. An unknown IF carrier can be estimated either with open loop (feed-forward) or closed loop (feedback). With an open loop estimation, a peak-seeking FFT with appropriate smoothing provides a good starting point for a digital PLL; with closed loop estimation, phase-increment detection provides high accuracy due to high sampling ratio.

For both analog and digital modulations, channel bandwidth needs to be estimated and adjusted in the cognitive receiver to match the incoming signal by adaptive filtering with demodulator feedback and symbol rate estimation.

3. MODULATION CLASSIFICATION FOR CR

3.1 Frequency, time, and vector domain signal analysis for modulation classification

Modulation classification consists of signal feature extraction and pattern recognition. Different algorithms are useful depending on which features are extracted. Modulation-related signal features are either waveform-level features extracted at digital IF or symbol-level extracted at baseband. For analog modulations, only waveform-level features are available; however, the modulation schemes are relatively easier to see because digital modulations can be classified at IF, baseband, or jointly.

Waveform-level features are either temporal or spectral. Due to the random nature of the modulated signal and the sinusoidal nature of the carrier, the received signal has cyclostationarity which can be represented in terms of statistical moments [7]. At the symbol level, not only instantaneous phase calculation but also signal constellation and rotation statistics on the complex plane can be effectively used to classify the modulation, especially for high-order quadrature modulations.

Temporal features
A modulated signal can be represented in complex format as:

$$s(t) = Re\{A(t)g(t)exp(j2\pi f(t) + \varphi(t))\} \qquad (1)$$

where $A(t)$ is the amplitude, $g(t)$ is the symbol pulse only existing in digital modulations, $f(t)$ is the frequency and $\varphi(t)$ is the phase. All temporal signal features are derived from these parameters [10] [11] [12].

Temporal feature-based modulation classification is straightforward and easy to implement. However, this feature set is typically sensitive to noise and distortion. The trade-off between feature robustness and computational complexity is the key, which will be detailed in our proposed signal classification approach in later sections.

Spectral features
Compared to temporal features, spectral features are more stable against noise. The classic spectral analysis is based on the fast Fourier transform (FFT) to estimate the signal's power spectral density (PSD) [13] [14]. Various averaging and windowing algorithms are proposed to achieve a balance between statistical stability and accuracy [15].

All human-made communication signals have cyclostationary nature, i.e., their statistical properties vary periodically with time. This inherent feature is modulation specific and robust against severe noise and moderate distortion and can be extracted by second-order frequency correlation [7]. Higher-order spectral calculations are also used to classify higher-order modulation schemes. However, the huge computational cost makes these approaches almost impossible for on-line processing.

Vector-space features

Vector analysis applies only for digital modulations whose complex symbol formats can be represented as constellations in the inphase/quadrature (I/Q) plane [8]. This provides a graphical insight into the underlying modulation schemes [6]. It is a by-product of demodulation, which is typically used for accurate phase estimation and fine tuning [16]. The vector space is calculated at symbol rates with much lower computational cost than digital IF processing.

The symbol constellation is naturally the major feature in vector space. Its statistical distribution and variation can be easily calculated and matched to the signature of the modulation scheme and channel properties. As the output of a baseband synchronizer, it is sensitive to frequency offset, noise, and distortion.

3.2 Feature recognition and pattern classification

In doing pattern classification, two general techniques have emerged: decision theoretic and pattern recognition. It has been shown that the decision theoretic work is not as robust or useful as the pattern recognition approach [17].

For the pattern recognition technique, there are various classification methods [18], among which artificial neural networks (ANN) [19] are the most suitable for signal classification. Their parallel distributed processing (PDP) structure provides flexibility and high reconfigurability for DSPs; their highly-connected network topology provides arbitrary nonlinear mapping for complicated signal feature sets; and their simple feed-forward calculation at each node (neuron) is suitable for on-line signal processing. ANNs can learn and adapt to complex, time-varying features and have fault tolerance, thus they are ideal statistical classifiers for modulation schemes [20].

4. COMPACT FEATURE SPACE AND OCON NEURAL NETWORK FOR MODULATION CLASSIFICATION

The design of an ANN-based classification system involves data acquisition, feature extraction and recognition, and decision making.

4.1 compact feature set in time-domain

Temporal feature extraction is a straightforward approach using signal waveforms at digital IF when signal quality is relatively good, i.e., with moderate noise and slight distortion. Although cyclostationary spectral features are more robust against lower SNR and larger distortion, the frequency correlation computation is intensive for blind classification without prior knowledge of frequency.

Temporal features are derived from the general format of a communications signal as in equation (1), which basically contains the statistics of a signal's amplitude, frequency, and phase variation.

Most modulation classifier systems in the literature are based on a standard set of features, with different ones added for specific modulation schemes. A typical feature set is listed in [4]. The features are statistical measures of these variations, where any given feature may be similar between different modulations but no two modulations are similar in all features. The choice of features is a trade-off between minimizing the number of features to reduce the ANN input size as well as computational complexity and including all necessary features for reliable modulation classification. A lot of previous work has already started to explore this trade-off [4] [17] [20].

The increase of feature set size significantly complicates the computation. It also takes a longer time for the network training process to converge. In our approach, we define five features, described by Equations (2) – (6).

The standard deviation of the direct value of the instantaneous amplitude:

$$\sigma_a = \sqrt{\left(\frac{1}{N}\sum_{n=1}^{N} A_n^2\right) - \left(\frac{1}{N}\sum_{n=1}^{N} A_n\right)^2} \tag{2}$$

The standard deviation of the envelope of the direct value of the instantaneous amplitude, where ENV is a block averaging of the amplitude:

$$\sigma_{ENV} = \sqrt{\left(\frac{1}{N}\sum_{n=1}^{N} ENV_n^2\right) - \left(\frac{1}{N}\sum_{n=1}^{N} ENV_n\right)^2} \tag{3}$$

The standard deviation of the direct value of the phase of the instantaneous signal:

$$\sigma_\varphi = \sqrt{\left(\frac{1}{N}\sum_{n=1}^{N} \varphi_n^2\right) - \left(\frac{1}{N}\sum_{n=1}^{N} \varphi_n\right)^2} \tag{4}$$

The standard deviation of the change in the phase of the instantaneous signal:

$$\sigma_{|\varphi|} = \sqrt{\left(\frac{1}{N}\sum_{n=1}^{N} \Delta\varphi_n^2\right) - \left(\frac{1}{N}\sum_{n=1}^{N} \Delta\varphi_n\right)^2} \tag{5}$$

The standard deviation of the absolute value of the change in the phase of the instantaneous signal:

$$\sigma_{|\Delta\varphi|} = \sqrt{\left(\frac{1}{N}\sum_{n=1}^{N} |\Delta\varphi|_n^2\right) - \left(\frac{1}{N}\sum_{n=1}^{N} |\Delta\varphi|_n\right)^2} \tag{6}$$

Note that these features only contain up to second-order statistics, and it is clear that phase information is emphasized because it is more sensitive to different

modulation schemes and less sensitive to white noise than instantaneous amplitude and frequency.

4.2 OCON neural network and system design

Most previous work on ANN modulation classification uses multi-layer perceptron networks (MLPNs) that trade network complexity and computational cost for flexibility and robustness in classification. Azzouz [4] uses a huge 3-layer MLPN, and two additional 2-layer MLPNs are added to distinguish specific modulation orders.

Modulation schemes are hidden in the received signals as second-order features which need strong nonlinear processing to extract. They can be grouped by their different modulating mechanisms, such as analog and digital modulation or frequency and phase-amplitude modulation, and these groups may be easily separated. However, similar modulations within the same group may only have subtle differences, and such differences are further corrupted by noise and distortion. All these effects make it difficult to apply a single, universal neural network for all the modulations under any scenario, even by expanding its size or using complicated neuron operations at each node.

We propose to look at each modulation in a different classifier sub-network. A one-class one-network (OCON) structure is created for each modulation type as shown in Figure 1. These networks each output a value, a probability of a match. The network with the highest output value is selected as the modulation type. Figure 1 shows a single OCON for one type of modulation. The other incoming lines to the MAXNET [21] are from other OCONs for the other modulation types. Each OCON is a simple MLPN with an input layer that takes five signal features and a single neuron output layer. Each OCON uses a radial basis function for pattern clustering. This system design is simple with small MLPNs and flexible since adding OCONs for new modulations is trivial.

The classification system is shown in Figure 2, where signal features are extracted after the analog signal is digitized at IF and passed through an OCON neural network, and the output is decoded into a modulation type.
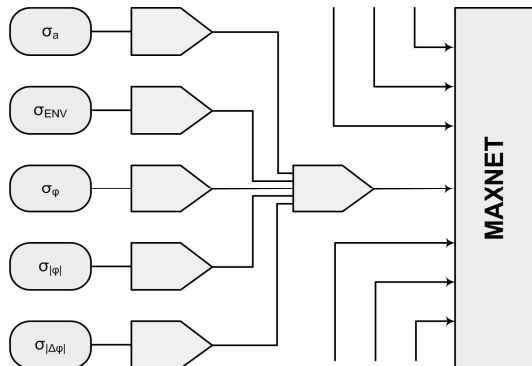
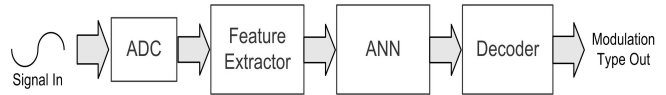

Figure 1. OCON for a modulation as input to the MAXNET.

Figure 2. Information flow for ANN modulation classifier.

5. SIMULATION AND PERFORMANCE ANALYSIS

We simulated the modulation classifier with seven modulations: AM, FM, BPSK, BFSK, QPSK, QAM8, and QAM16, which are typical modulations used in narrowband wireless communications. We evaluated the performance by creating real-world signals that were band limited and the digital signals were pulse shape filtered. We also investigated the performance dependency on different SNR values in an additive white Gaussian noise (AWGN) environment. We used SNR values of 50, 20, 10, and 0 dB as well as a low-noise system (100 dB) as a baseline. Table 1 lists the success rate of classification for all SNR values.

Table 1. Success Rate of Classification

| Modulation | Probability of Success for SNR | | | |
	10 dB	20 dB	50 dB	100 dB
AM	94.0	99.0	100.0	99.0
FM	100.0	100.0	100.0	100.0
BPSK	100.0	100.0	100.0	100.0
QPSK	64.0	86.0	92.0	90.0
BFSK	43.0	100.0	100.0	100.0
QAM8	34.0	34.0	62.0	59.0
QAM16	67.0	64.0	73.0	88.0
Overall	68.7	83.3	89.6	90.9

The analog modulation information was generated by taking an audio waveform using MATLAB, sampled at 8 kHz. The digital modulation information was generated as a pseudorandom sequence of bits with a rate of 1 kbps. The symbols were shaped using a square root raised cosine filter with a 0.5 roll-off factor. A total of 800 signals of each modulation type were created to the above specifications. One hundred of these signals were used to train each OCON and 700 signals were used in the testing of the parallel system.

Training took thirty thousand iterations in twenty minutes, which was well beyond what was required as about 90% of the optimization of the networks was done in the first ten thousand iterations. The remaining fifteen or so minutes only trained another 10%. In this network, training is performed off-line, and the operational question is the length of time required to classify a newly observed signal. In the MATLAB simulation, the average time to classify is 0.01 seconds for feature extraction and 0.025 seconds for classification. The time requirement would be greatly reduced in a live system because it would be executed on a more computationally efficient platform in compiled form.

The overall probability of successfully classifying any signal is over 80% for 20 dB SNR and above. This is comparable with the results presented in many of the papers reviewed. However, on closer inspection, we note that most of the confusion occurs when trying to differentiate between the quadrature modulation signals, QPSK, QAM8, and QAM16. Removing these from the system (as some previous work does) dramatically increases the overall probability of successful classification. The next section provides insight into how the neural network actually works.

5.2 Feature space analysis

For illustration, only the 100 dB SNR (low-noise) and 10 dB SNR (noisy) results are compared, but the analysis applies to any SNR. The entire feature set consists of average standard deviation values for one hundred signals.

The feature space with multiple feature dimensions is the basis of pattern classification by neural networks, which is how the OCON is able to distinguish different modulation types. While certain features group modulation types together, other features help separate them. We explain the feature space by plotting subgroups of the feature set and show how different signals may be classified by the neural network's clustering nature.

Figure 3 plots a feature sub-space of the standard deviation of the amplitude versus the standard deviation of the differential phase at 100 dB and 10 dB SNR. All modulations in the following plots use the same color and symbol convention. The low-noise signals in Figure 3 illustrate how easily BPSK, FM, BFSK, and AM are differentiated. They exist in different sections of the feature space and can easily be distinguished with a radial basis function mapping. Conversely, QPSK, QAM8, and QAM16 lie very close to each other, making separation difficult.

To see how added dimensionality increases the ability of the system to separate modulations, we look at a three-dimensional plot of the standard deviation of amplitude, envelop, and differential phase, as shown in Figure 4 with both the 100 dB and the 10 dB SNR signals. Specifically, Figure 4a shows how in three dimensions, the QPSK, QAM8, and QAM16 signals distinguish themselves more
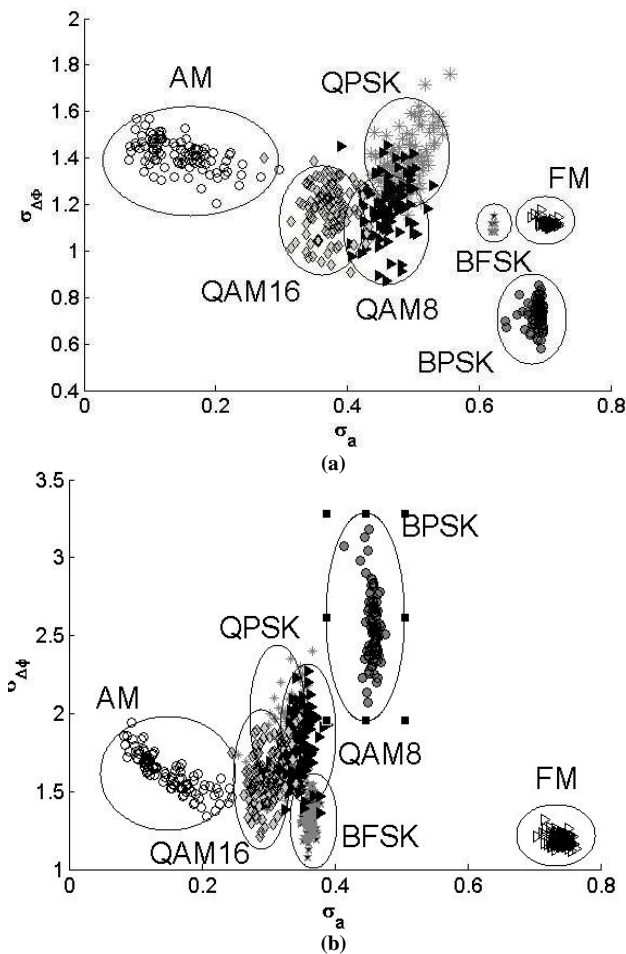

Figure 3. Feature Space for standard deviation of amplitude versus differential phase for (a) 100 dB and (b) 10 dB SNR.
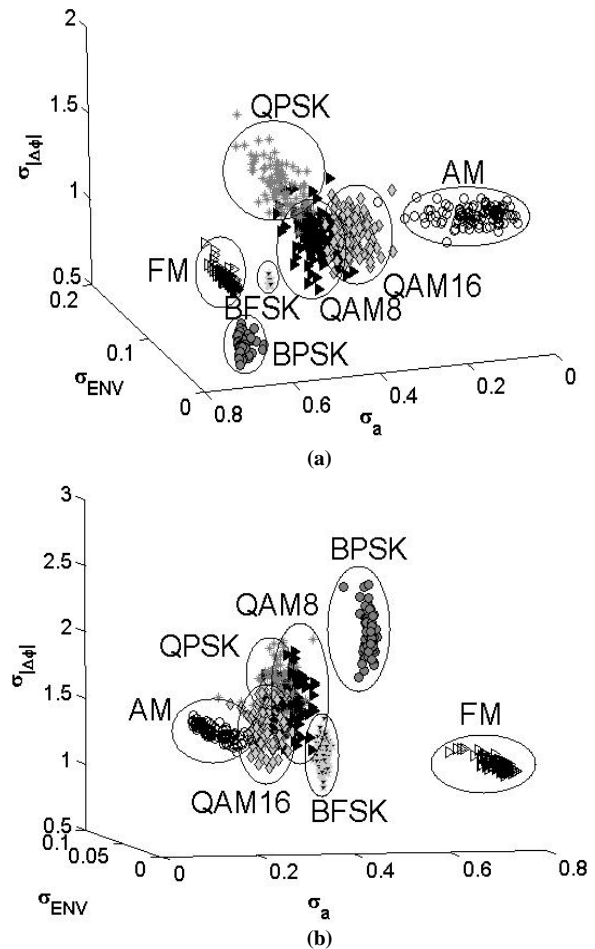

Figure 4. Feature space for the standard deviation of amplitude, envelope, and differential phase for (a) 100 dB and (b) 10 dB.

than in two dimensions. Figure 4b confirms the problems with added noise and again shows how the QPSK, QAM8, and QAM16 crowd together due to noise.

It is difficult to separate high-order modulations such as QAM8 and QAM16 unless high-order statistical moments are calculated to "extract" the modulation-specific information for feature clustering. In the previous work, simple systems ignored these modulations, and complex systems traded high computational cost for acceptable performance.

6. CONCLUSION AND FUTURE WORK

One contribution to the signal classification system in this paper is the new network design using the parallel OCONs as opposed to a single MLPN. Our design allows great flexibility and on-line updates of classification systems as new modulation classification is required and developed. Another contribution is the analysis of the signal feature space for various modulation schemes.

While we have analyzed an OCON-ANN classifier for seven different modulations, this work is not without its problems and room for improvement. Specifically, we have shown the difficulty in distinguishing between the QAM modulations. More work needs to be done to find the optimal feature set for all of the modulations. The goal is to use the minimum number of features with the least computational cost.

Our work in this paper lacks an analysis of channel conditions other than AWGN and focuses on narrowband signals. Multipath fading and interferences, although these may be alleviated by equalization, make classification difficult. The current research is directed to design the complete cognitive wireless receiver that provides a system solution of waveform recognition from RF to baseband, as stated in the beginning sections. An additional goal is to build a system that can classify all existing/overlapping signals because we do not know which signal is the desired one. Spread spectrum and ultra-wideband signals offer even greater challenges to the operation of a modulation classifier.

7. ACKNOWLEDGMENTS

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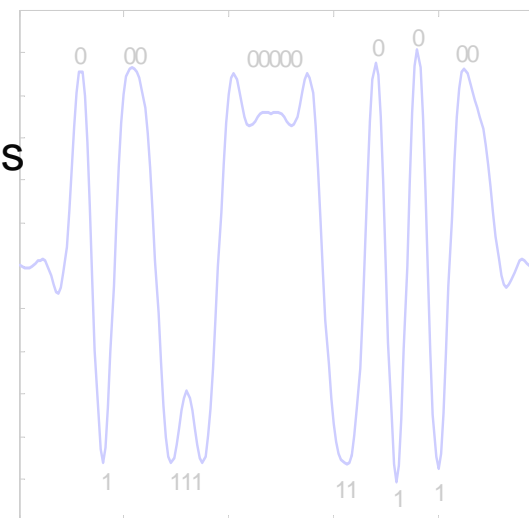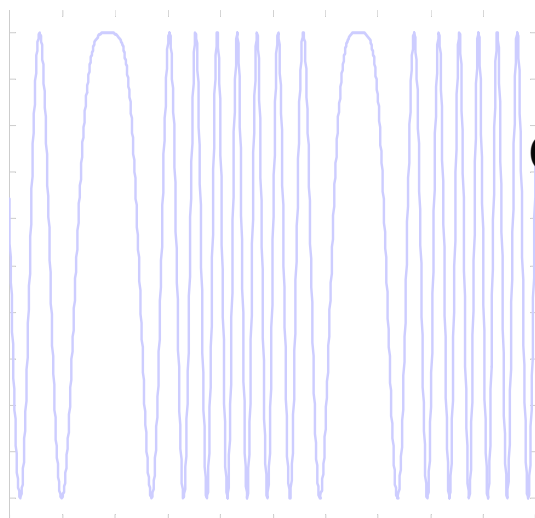
Modulation Identification Using Neural Networks for Cognitive Radios

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Presentation Outline

- Cognitive radio (CR) overview

- Synchronization for CR

- Modulation classification

- Neural network for modulation identification

- Waveform feature space analysis

Cognitive Radio

- Cognitive radios (CRs) are intelligent communications devices that are aware of the external environment and user needs to reconfigure themselves to optimize quality of service (QoS).

- Physical (PHY) and MAC layer agility

- Cross-layer performance optimization

Radio Environment Awareness

- Radio-domain cognition – a low-layer intelligence over SDR platform

- Propagation channel modeling and tracking

- Spectrum sensing and understanding

- Waveform recognition and modulation identification

I don't understand the meaning of "low-layer intelligence over SDR platform". Do you mean "…intelligence supervising the SDR platform"?

Universal Waveform Recognition

- Standard-based or standard-free waveform recognition
- System-wide cognitive receiver design
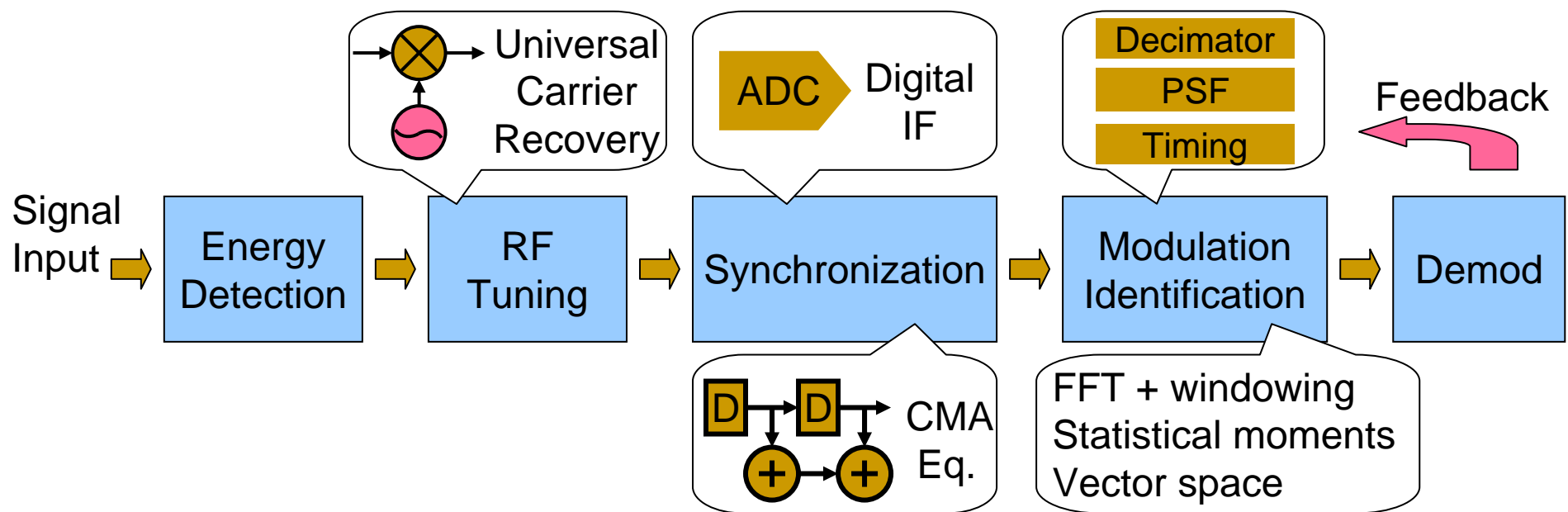
General Synchronization Design Challenge

- Carrier recovery is modulation-specific or pilot-aided

- Symbol timing is data-aided

- Equalization is based on known link standard

- Demodulation is after known matched filter

- System-level design reform is needed for universal synchronization

Communication Signal Analysis Methods

- ## A hybrid, hierarchical signal feature classification approach is designed
  - Where: digital IF and baseband
  - Methods: temporal, spectral, and vector space
  - How: using neural network for signal classification
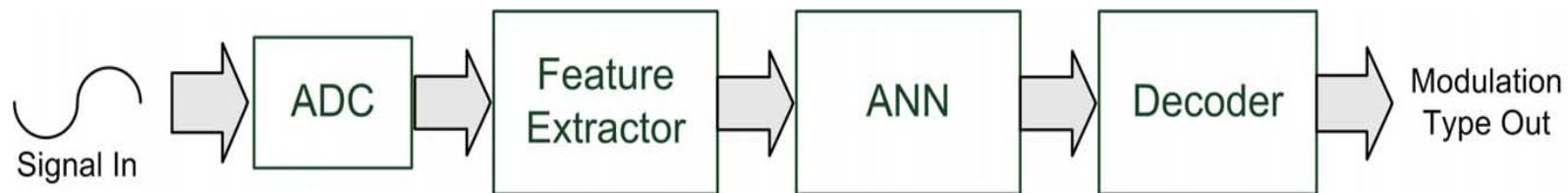
Waveform Features

- **Temporal statistical features**
  - Statistical moments with different orders
  - User-defined metrics based on basic statistics

- **Spectral statistical features**
  - Power spectral density (PSD)
  - Cyclostationarity features

- **Vector-space features**
  - Constellation distribution
  - Complex phase swing and rotation

Design Considerations

- Suitability for embedded DSP

- Efficiency for low-power on-line processing

- Adaptation for wireless channel variations

- Flexibility for reconfigurability and hardware compatibility

- Robustness for reliable performance

Modulation Classifier Options
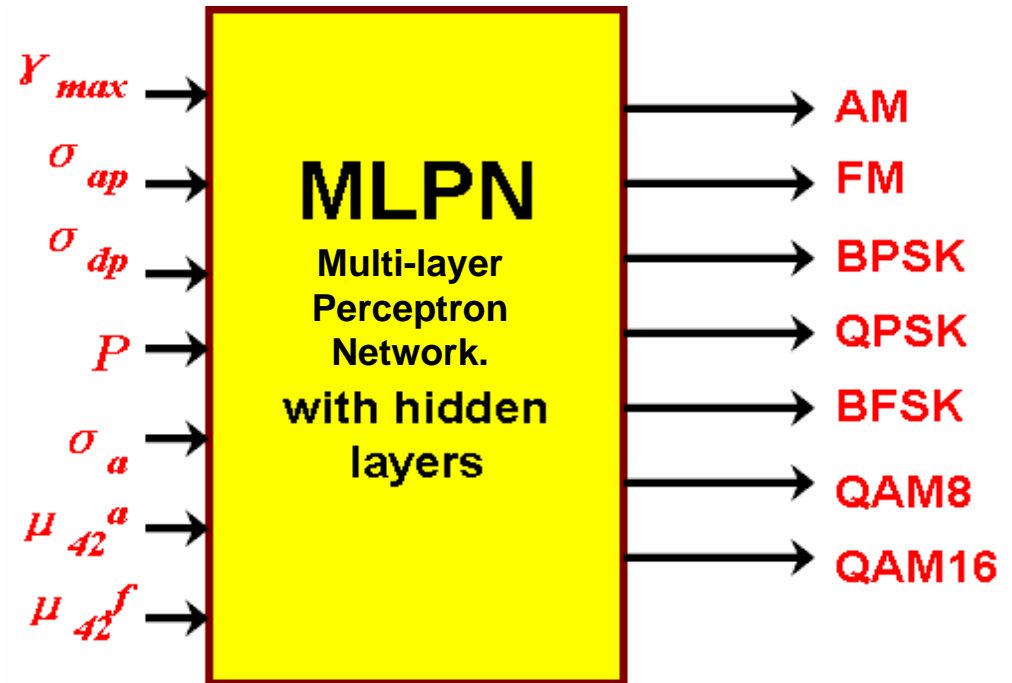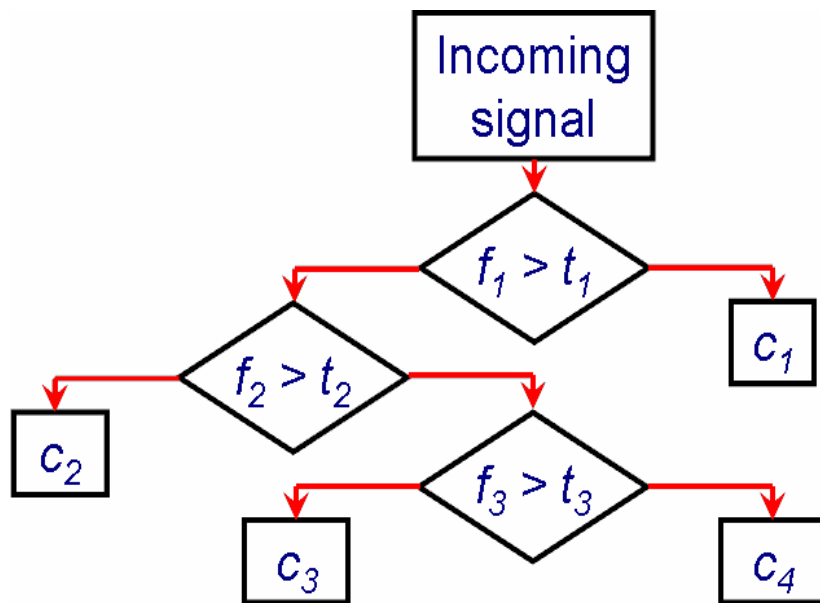
- **Decision theoretic**
  - Threshold control
  - Error misleading
  - Difficult to reconfigure

- **Ad-hoc direct classify**
  - Input encoding
  - Training needed
  - Network configuration

Neural Networks for Direct Classification

- Parallel distributed processing (PDP) nature
- Flexibility in topology and connection configuration
- Arbitrary nonlinear mapping capability
- Simplicity for on-line processing
- Self-learning and adaptation
- Robust against noisy inputs

One-class-one-network (OCON)

- **Multi-layer perceptron network (MLPN)**
  - Large, heavy computation, slow
- **OCON with maxnet decision maker**
  - 2-layer (5+1) small sub-net for each modulation
  - Simple voting at maxnet output
  - Easy to reconfigure, and VERY fast
  - Ideal for DSP implementation
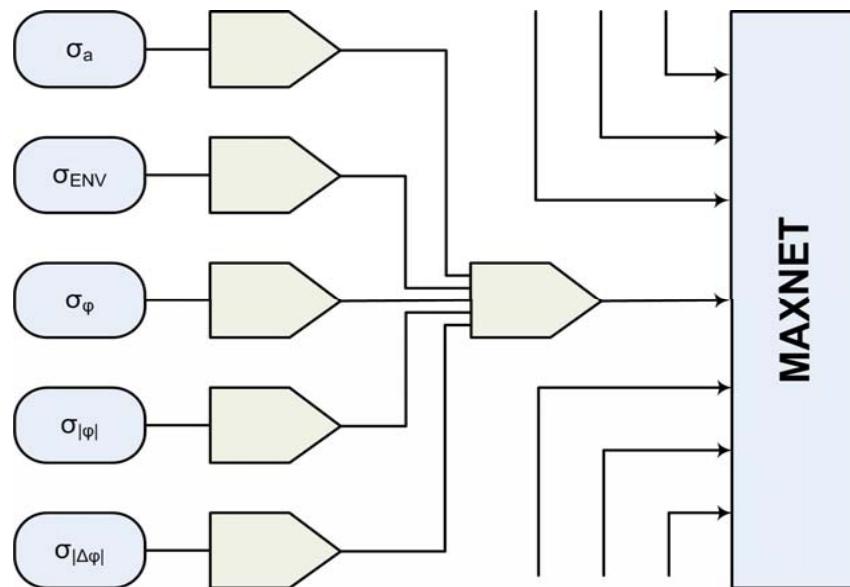
Waveform Features

$$s(t) = A(t)g(t)\cos(2\pi f(t)t + \phi(t)) = A(t)g(t)\operatorname{Re}\left\{ e^{j\phi(t)} e^{j2\pi f(t)t} \right\}$$

- Modulating mechanisms define how amplitude, frequency and phase vary, not their values
- Waveform changes in time and frequency
- Signal constellation moves in real and complex domain
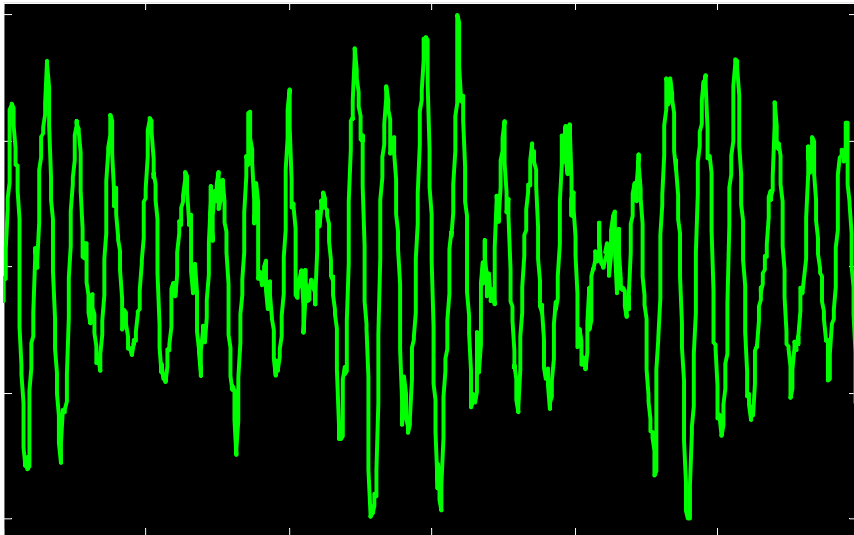
AM (modulation index =1)
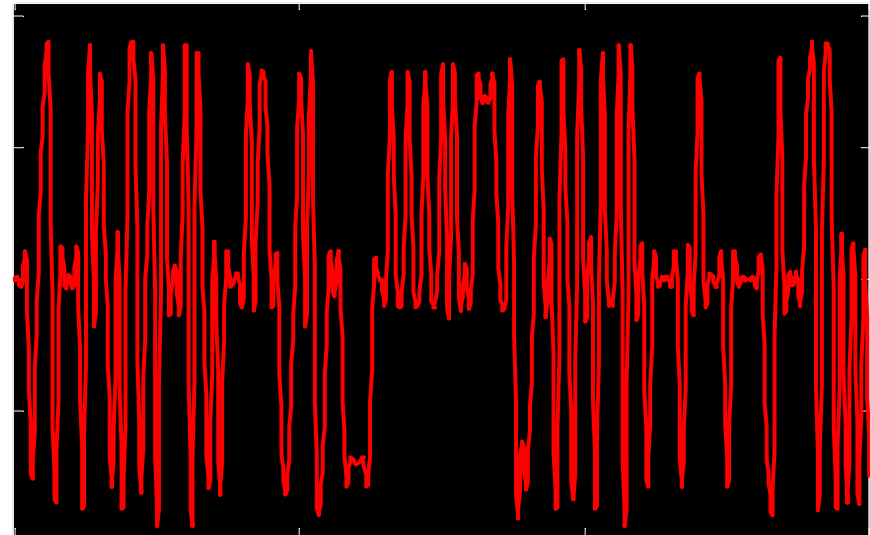
BPSK (pulse-shaping roll-off = 0.5)

Waveform Features in Time Domain

σ_a - Standard deviation of the signal amplitude

σ_{ENV} - Standard deviation of signal envelope

σ_{Φ} - Standard deviation of the phase

$\sigma_{\Delta\Phi}$ - Standard deviation of the change in phase

$\sigma_{|\Delta\Phi|}$ - Standard deviation of the absolute value of the phase change

- Only five basic statistics need to be calculated
- Represent up to second-order statistics   It isn't clear to me what this means
- Phase information is emphasized because
  - More sensitive to different modulation schemes
  - Less sensitive to noise than instantaneous amplitude and frequency
- In MATLAB, the average time to classify is 0.01 seconds for feature extraction and 0.025 seconds for classification

A Typical Performance with AWGN

Table 1. Success Rate of Classification

Probability of Success for SNR

Modulation	10 dB	20 dB	50 dB	100 dB
AM	94.0	99.0	100.0	99.0
FM	100.0	100.0	100.0	100.0
BPSK	100.0	100.0	100.0	100.0
QPSK	64.0	86.0	92.0	90.0
BFSK	43.0	100.0	100.0	100.0
QAM8	34.0	34.0	62.0	59.0
QAM16	67.0	64.0	73.0	88.0
Overall	68.7	83.3	89.6	90.9

What causes the problem at low SNR ?

Modulation Schemes in Feature Space
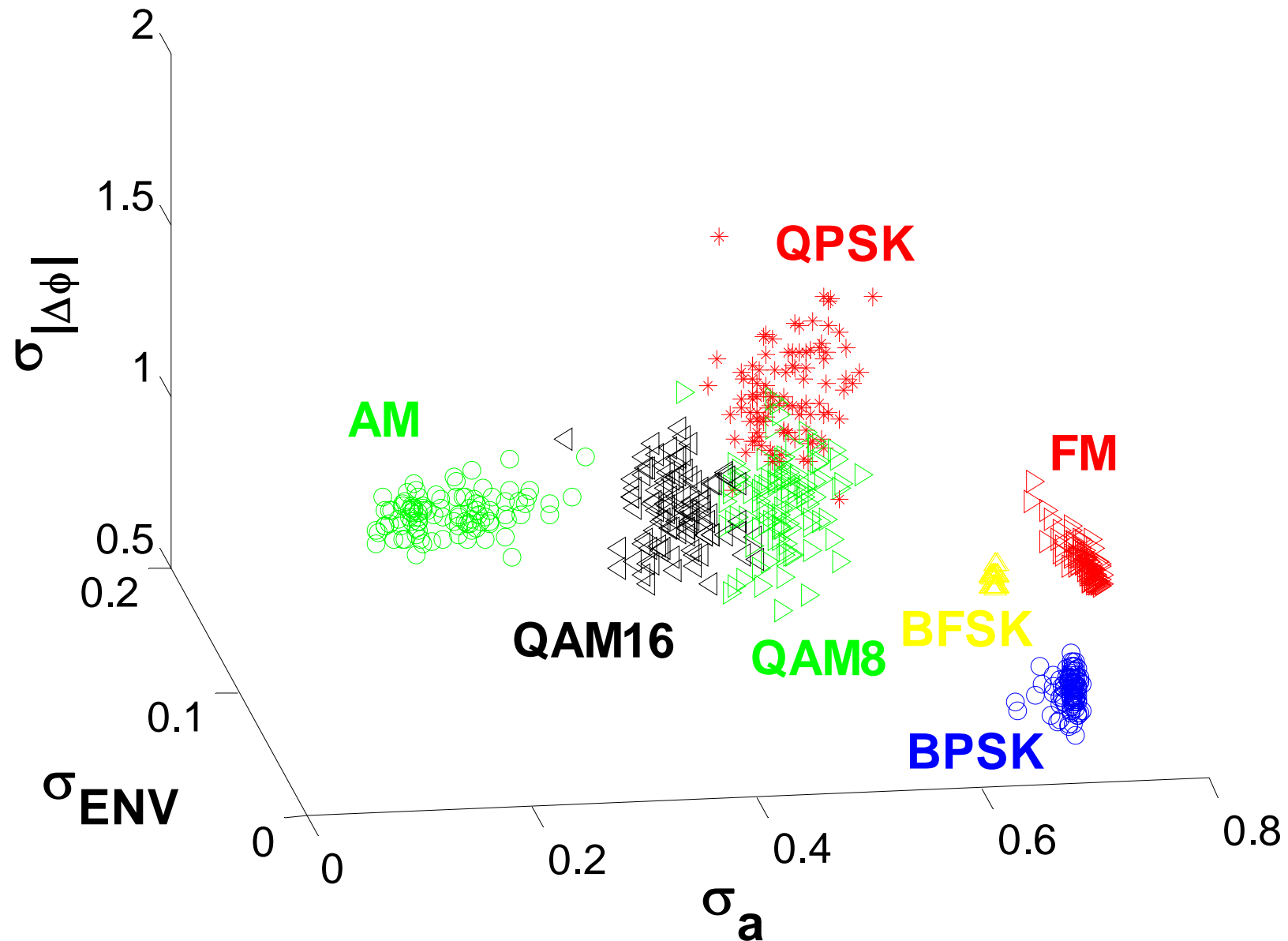
Modulation Schemes in Feature Space
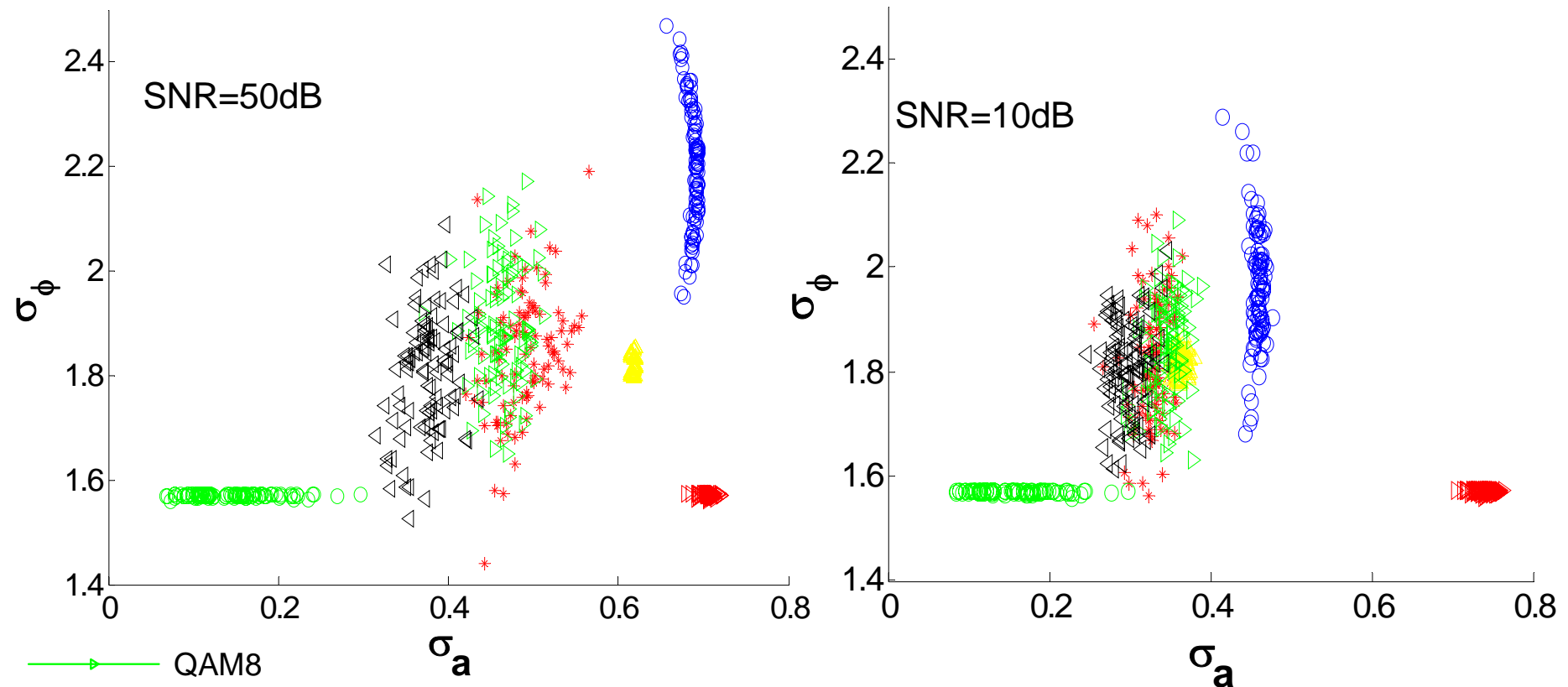
- Separation reduced by noise
- Differentiation is determined by feature space definition
- Trade-off between computational cost and performance
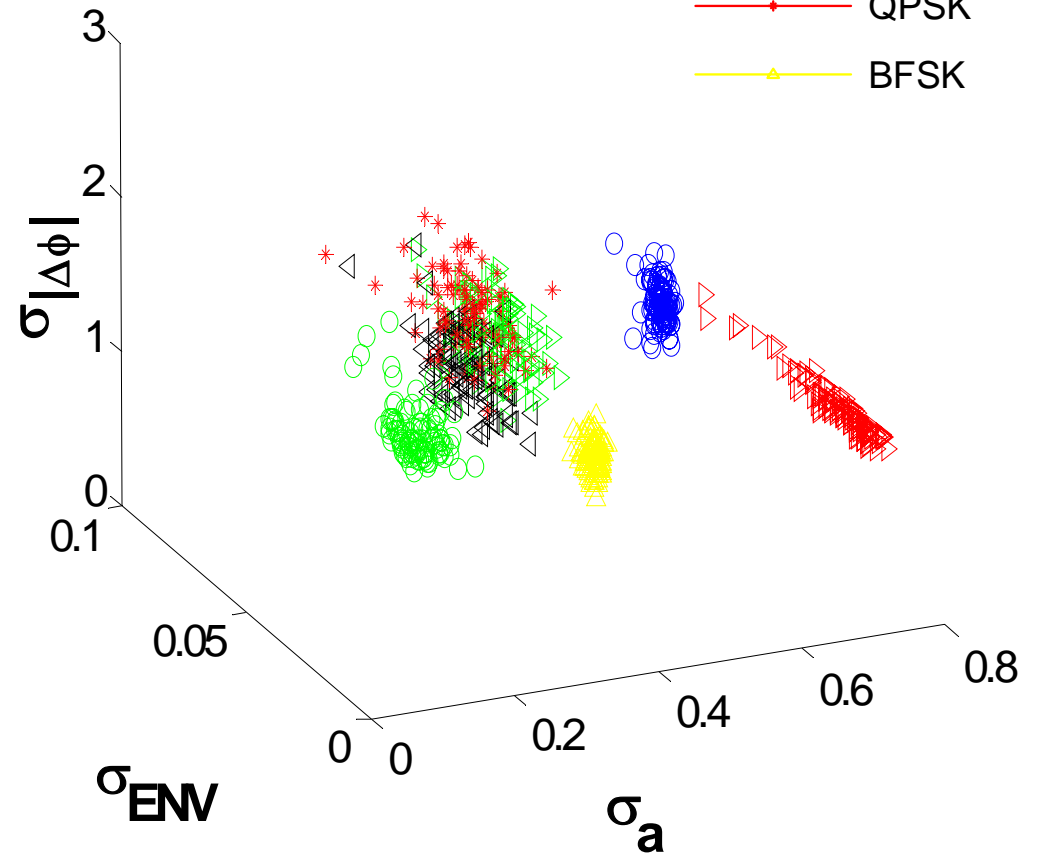- Trade-off between network size and nonlinearity

How Dimension Helps

Modulation signals at SNR = 10 dB :
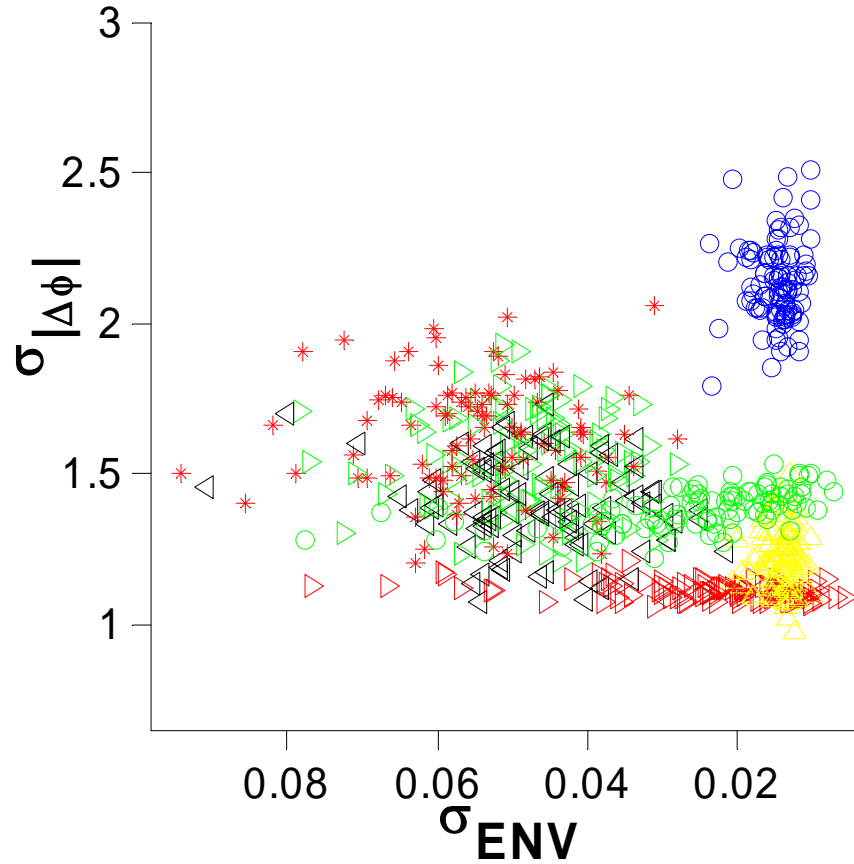
Two-dimension feature sub-space

Three-dimension feature sub-space

Status of Work

- New network design of parallel OCONs as opposed to conventional single MLPN

- Analysis of the signal feature space for various modulation schemes that no paper did before

- Illustration of the difficulty in QAM modulations that no paper explained before

- Combinatorial signal identification approach is under CWT's current research

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