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Survey of Methodology and Features for Radar Waveform Modulation Classification

by Kwok Tom and Kenneth Ranney

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14. ABSTRACT
Researchers at the US Combat Capabilities Development Command Army Research Laboratory recently performed a survey of pulse identification techniques presented in the open literature. This effort represents the first step in the development of a capability to automatically identify arbitrary radar pulses.

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Contents

1. Introduction

Researchers at the US Combat Capabilities Development Command (CCDC) Army Research Laboratory (ARL) recently performed a survey of pulse identification techniques presented in the open literature. This effort represents the first step in the development of a capability to automatically identify arbitrary radar pulses. As part of this effort, a survey of intra-pulse modulations classification techniques was conducted. This report provides a summary of the open literature on radar pulse modulation classification.

Many different approaches have already been investigated, some attempting to characterize pulse modulation and others attempting to identify the radar system based on measured parameters such as operating frequency and pulse shape parameters. The majority of the open modulation classification literature deals with classification of communications signals. Some of the classification techniques and features are applicable to radar signals. In some of these cases, a preprocessing stage must be included to extract the pulse data input to provide intra-pulse modulation recognition.

In what follows, we summarize many technical approaches used to provide modulation classification found in the open literature. We begin with a general summary of processing techniques that are drawn from many mathematical and engineering fields. These classification techniques are drawn from the fields of statistics, domain transformations, digital signal processing, image processing, pattern recognition, machine learning algorithms, and artificial neural networks. In many cases, there is significant integration of processing techniques from various scientific fields. A list of references is included at the conclusion of the paper.

Digital techniques have given radar configuration more flexibility and adaptability in operations. Advances in hardware components, RF and signal processing hardware, and signal processing algorithms have provided a more advanced capability that has necessitated the inclusion of more advanced techniques to identify and classify the radar configuration.

2. Specific Emitter Identification (SEI)

Historically, SEI has been based on physical parameters that could be measured on the radar return such as pulse repetition interval (PRI), pulse width (PW), pulse rise and fall time, and operating frequency. Due to the limited number of radar systems, the types of measurements were sufficient to identify the radar types. Radar system configurations were designed for the basic operation of target detection. As technology advanced in RF components, electronic components, computer processing and control, and modulation complexity, radar identification has become increasingly difficult. The new low probability of intercept (LPI) radars are designed to make their detection harder or impossible.

2.1 SEI with Cumulants Features

The classic approach to SEI relies on the basic parameters of the radar pulse signal. Under this approach, it can distinguish among radar systems that appear to be identical. A more effective implementation would be to exploit differences in the radars' unintentional modulations on pulse (UMOP). Basically, the goal is to assign a fingerprint to the radar signal to uniquely identify the radar source to produce an effective SEI capability.

Aubry et al.[1] developed an improved SEI system by identifying an additional set of features of the radar signal. This new set of features is based on the use of high-order statistics (HOS). Specifically, the authors examined the use of the cumulants features of the intercepted signal. The goal was to identify relevant features that have some desirable robust characteristics such as shift invariance, noise invariance, and scale invariance. The second-, third-, and fourth-order cumulants were identified as being effective. Cumulants of an order greater than 2 share the shift- and noise-invariant properties. In addition, these cumulants were normalized to provide for the invariant-property goal.

The k-nearest neighbor (KNN) classifier was chosen to sort the emitter signal into the appropriate class. Evaluation of this system was performed on a real data set. Three airborne radar signals (same model) were acquired by Elt_Elettronica SpA. The results from the classifier were considered very good, although not perfect.[1]

2.2 SEI Based on the Deep Belief Network (DBN)

The traditional SEI method employs the characteristic parameters, such as the time of arrival (TOA), direction of arrival (DOA), RF, PRI, and PW of the radar signal. Radar emitter recognition is difficult to accomplish with these parameters alone. Other parameters, such as the unintentional modulation of the radar pulse, are noted, including pulse leading edge characteristics, phase noise, and frequency drift.

Dong et al.[2] exploited the unintentional modulation of radar signals by the radar transmitter. Their focus was on using pulse envelope distortion as a parameter in the recognition process. Instead of developing/extracting features from the pulse directly, their effort examined the use of a neural network to identify the features directly and autonomously from the time-domain data sequence. Using this technique, they reduced the dependence on prior knowledge and developed discriminate features.

A DBN was used in their research. This neural network architecture uses is a deep structure superposed by multilayer limited Boltzmann machines. Compared with the traditional shallow network, the DBN process exhibits superior feature extraction and dimension reduction. The research was executed with computer simulations. Four different types of leading-edge shapes were modeled. Unsupervised extraction of the pulse leading edge was conducted in the time domain. Fine-tuning of the network was conducted with supervised adjustment based on the labeled data. The advantage of the method is that it overcomes the complexity of artificial feature extraction and extracts the deep features of the radar signal in the time domain. A comparison was conducted that showed improvements over other classification techniques. However, this study only examined signals with a signal-to-noise ratio (SNR) of 10 dB.[2]

2.3 SEI with Linear Discriminant Analysis (LDA) and Karhunen–Loève Transformation (KLT)

Kawalec et al.[3] provided a technique to improve on the SEI process. The early SEI process dealt with the inter-pulse measurement parameters such as TOA, PW, amplitude (A), RF and carrier frequency, and frequency modulation on pulse (FMOP). An issue with this paradigm is that it cannot distinguish between radar devices of the same type.

To overcome the problem, the authors incorporated a parameter that considers the individual pulse or intra-pulse information. An overview of the procedure/ methodology used in enhancing the classification was provided. Their method is a composite task that involves pulse measurements, features extraction, normalization, selection, classification (recognition), and verification. Features were generated and two typical machine learning algorithms were employed for feature selection: LDA and KLT (i.e., principal component analysis). Comparison of the two data-reduction algorithms yielded similar results for feature reduction. Actual experiments were conducted where about 1 million pulses from 62 emitters were evaluated against their classifiers. The classifier demonstrated a significant improvement in accurately identifying emitters with the additional intra-pulse features.[3]

3. Signal Processing Techniques

3.1 Hilbert Transformation

The Hilbert transform is important signal processing trick wherein the analytic signal is derived from a real-valued signal. For a system capable of a measuring only a single channel, the signal is considered a real-valued signal as function of time. The Hilbert transform creates a complex representation of the signal in that the real-valued measurement is labeled as the "in phase" component. The "quadrature" component is generated by introducing a phase shift in the in-phase component by $\frac{\pi}{2}$. The combination of these two components defines the analytic function. If the radar measurement has a complex representation, the Hilbert transform is not necessary. Calculation of the instantaneous amplitude and frequency constitute a critical basis for determining key modulation features.

3.2 Convolution

Convolution is a simple mathematical operation that is fundamental to signal and image processing operators. Convolution provides a way of "multiplying together and integrating" two arrays of numbers, generally of different sizes but of the same dimensionality, to produce a third array of numbers of the same dimensionality. For a linear system, if the input sequence and impulse response of the system is known, the output sequence can be computed. In this case, the convolution process involves multiplication and summation of the two signals with one of the signal reversed. This is expressed as

$$[f * g] = \int_{0}^{\tau} f(\tau)g(t-\tau)d\tau \tag{1}$$

where f and g can represent the input and impulse response.

In image processing, the convolution processing is similar, except that there is no reversing of any of the data matrix pixels. For a convolutional neural network (CNN), the input is the image and it is convolved with a matrix that is smaller in size. This smaller matrix is also known as a filter or kernel. It is basically a "dot product" between the image and filter, as the filter output is computed as it slides across the image to yield a single value for each position. The calculation is a summation and element multiplication between the image and the corresponding location of the kernel as expressed by

$$C[m,n] = \sum_u \sum_v A[m+u, n+v] \cdot B[u,v] \tag{2}$$

where C is the output image, A is the input image, and B is the kernel.

3.3 Instantaneous Frequency and Phase

Let the complex signal be representative as

$$\hat{s} = x + iy \tag{3}$$

The instantaneous phase of the complex signal is the complex argument function defined as

$$\phi(t) = arg\{\hat{s}\} = tan^{-1}\left(\frac{y}{x}\right) \tag{4}$$

There are two categories that define the range of the instantaneous phase value: “wrapped phase” and “unwrapped phase”. For “wrapped phase”, the instantaneous phase calculation ranges between values of $[-\pi, \pi]$. In the case for “unwrapped phase”, the instantaneous phase is represented as a continuous function. When the calculation of adjacent difference points exceeds a value of π radians, a value of 2π phase is added to the instantaneous phase calculation at that position forward.

The instantaneous frequency is the rate of change of the instantaneous phase. Instantaneous frequency (angular) can be expressed as follows:

$$\omega(t) = \frac{d\phi(t)}{dt} \tag{5}$$

and the instantaneous frequency (regular) is defined as

$$\begin{aligned} f(t) &= \frac{1}{2\pi}\omega(t) \\ &= \frac{1}{2\pi}\frac{d\phi(t)}{dt} \end{aligned} \tag{6}$$

where $\phi(t)$ must be the unwrapped instantaneous phase angle. It can be approximated using the finite difference equation as

$$f(k) = \phi(k+1) - \phi(k) \quad (7)$$

where $\phi(k)$ is the unwrapped instantaneous phase.

4. Features

Modulation recognition has been conducted for many decades. Fundamentally, the research was performed on communications-type signals. Initially, these signals were analog signals: amplitude and frequency modulations. As the hardware technology has evolved, the different types of communications modulation have evolved and become more complex in nature. The introduction of digital techniques has created many forms of modulation for communications.

Initial radar signals evolved from continuous-wave to pulse-radar signals in order to obtain range resolution. Detection of targets is the main purpose of radar systems, as indicated in the name, which is an acronym for *ra*dio *d*etection *a*nd *r*anging. Originally, it was necessary to transmit high power levels in order to obtain the desired range response, but this approach is susceptible to counterattacks since the radar could also be easily detected. LPI radar techniques evolved to reduce radar detectability. The LPI transmitter energy is reduced and spread over a larger frequency band of operation. Spreading the energy over a larger PW reduces the range resolution compared to a shorter PW signal. This is mitigated by modulating the intra-pulse signal (i.e., the signal within the pulse). Through signal processing techniques, the increased range resolution is obtained.

Some of the foundational work was performed by the following authors: EE Azzouz and AK Nandi. Their work[4] dealt with the modulation of communications-type signals. A significant number of researchers expanded on the feature basis that Azzouz and Nandi created. These features are formed using basic statistical measures on the normalized instantaneous amplitude, frequency, and phase. The five features that they proposed are as follows.

4.1 Maximum Fourier Transform of the Normalized-Centered Instantaneous Amplitude

The maximum Fourier transform of the normalized-centered instantaneous amplitude is

$$\gamma_{max} \triangleq max\left|DFT\left(A_{cn}(i)\right)\right|^2 \quad (8)$$

where $A_{cn}(i)$ is the value of the normalized-centered instantaneous amplitude at time instants $t = \frac{i}{f_s}$ $(i = 1,2, \dots N)$ and it is defined by

$$A_{cn}(i) \triangleq A_n(i) - 1 \tag{9}$$

$$A_n(i) = \frac{A(i)}{\mu_a} \tag{10}$$

where μ_a is the average value of the instantaneous amplitude over one frame, that is,

$$\mu_a = \frac{1}{N}\sum_{i=1}^{N} A(i) \tag{11}$$

Normalization of the instantaneous amplitude is necessary in order to compensate for the channel gain. Thus, γ_{max} represents the maximum value of the spectral power density of the normalized-centered instantaneous amplitude of the intercepted signal.

4.2 Standard Deviation of the Nonlinear Component of the Absolute Instantaneous Phase

The standard deviation of the nonlinear component of the absolute instantaneous phase is

$$\sigma_{ap} \triangleq \sqrt{\frac{1}{C}\left[\sum_{A_n(i)>a_t} \phi_{NL}^2(i)\right] - \left[\frac{1}{C}\sum_{A_n(i)>a_t} |\phi_{NL}(i)|\right]^2} \tag{12}$$

where $\phi_{NL}(i)$ is the value of the nonlinear component of the instantaneous phase at the time instants $t = \frac{i}{f_s}$, C is the number of samples in $\{\phi(i)\}$ for which $A_n(i) > a_t$, and a_t is a threshold for $A(t)$ below which the estimation of the instantaneous phase is very sensitive to the noise. Thus, σ_{ap} is the standard deviation of the absolute value of the nonlinear component of the instantaneous phase, evaluated over the nonweak segments of the intercepted signals.

4.3 Standard Deviation of the Nonlinear Component of the Instantaneous Phase

The standard deviation of the nonlinear component of the instantaneous phase is

$$\sigma_{dp} \triangleq \sqrt{\frac{1}{C}\left[\sum_{A_n(i)>a_t} \phi_{NL}^2(i)\right] - \left[\frac{1}{C}\sum_{A_n(i)>a_t} \phi_{NL}(i)\right]^2} \tag{13}$$

Thus, σ_{dp} is the standard deviation of the nonlinear component of the direct (not absolute) instantaneous phase, evaluated over the nonweak segments of the signals.

4.4 Standard Deviation of the Absolute Normalized Instantaneous Amplitude

The standard deviation of the absolute normalized instantaneous amplitude is

$$\sigma_{aa} \triangleq \sqrt{\frac{1}{N}\left[\sum_{i=1}^{N} \left|{A_{cn}}^2(i)\right|\right] - \left[\frac{1}{N}\sum_{i=1}^{N} |A_{cn}(i)|\right]^2} \tag{14}$$

The fourth key feature, σ_{aa}, is the standard deviation of the absolute value of the normalized-centered instantaneous amplitude of the signal.

4.5 Standard Deviation of the Absolute Value of the Normalized Instantaneous Frequency

The standard deviation of the absolute value of the normalized instantaneous frequency is

$$\sigma_{fa} \triangleq \sqrt{\frac{1}{C}\left[\sum_{A_n(i)>a_t} f_N^2(i)\right] - \left[\frac{1}{C}\sum_{A_n(i)>a_t} |f_N(i)|\right]^2} \tag{15}$$

where the centered instantaneous frequency f_c is normalized by the bit rate, r_b, to obtain f_N according to

$$f_N[i] = \frac{f_c[i]}{r_b} \tag{16}$$

At this point, the referred centered instantaneous frequency f_c is denoted by the mean value of frequencies constituting the pulse modulation. It is given by

$$f_c[i] = f[i] - \mu_f \tag{17}$$

$$\mu_f = \frac{1}{N}\sum_{n=1}^{N} f[i] \tag{18}$$

where N is the number of frequency-domain samples. σ_{fa} is the standard deviation of the absolute value of the normalized-centered instantaneous frequency, evaluated over the nonweak segments of the intercepted signal.[4]

Lunden and Koivunen[5] developed feature set designed for radar platforms. The received signal is a discrete-time complex signal as represented by

$$y(k) = x(k) + n(k) = Ae^{j\emptyset(k)} + n(k) \tag{19}$$

where $y(k)$and $x(k)$ are the complex envelopes of the intercepted and transmitted signals, respectively, and $n(k)$ is the (complex) noise. In complex polar form, A is constant amplitude and $\emptyset(k)$ is the instantaneous phase of the complex envelope.

4.6 Second-Order Statistics Features

Second-order statistical features were implemented through the use of moments and cumulants. These second-order features provide good recognition of binary phase signals. The squared complex envelope of a binary phase signal has a useful property in that it is a constant.

The general form of the moment statistic of the complex envelope of a complex random process $y(k)$ may be estimated as

$$\widehat{M_{nm}} = \left|\frac{1}{N}\sum_{k=0}^{N-1} y^{n-m}(k)(y^*(k))^m\right| \tag{20}$$

where N is the number of data samples and m is the number of conjugated components. The use of the absolute value renders the estimate invariant to constant phase rotation. Another way to obtain scaling invariance is through the normalization of the input sequence, $y(k)$, prior to applying moment. Scaling invariance is expressed as follows:

$$\tilde{y}(k) = \frac{y(k)}{\sqrt{\widehat{M_{21}} - \sigma_n^2}} \tag{21}$$

where σ_n^2 is the variance of the additive noise.

The first- and second-order moments $\widehat{M}_{10}$ and $\widehat{M}_{20}$ as well as the second-order cumulant $\hat{C}_{20}$ were chosen as features. $\hat{C}_{20}$ is calculated similarly as $\widehat{M}_{20}$, except that the mean $\widehat{M}_{10}$ is first subtracted from $y(k)$.

4.7 Power Spectral Density (PSD) Features

The signal power distribution in the frequency domain is obtained through the Fourier transform. Two additional features are formed through the PSD. The first feature is the maximum of the PSD of the complex envelope as expressed as

$$\gamma_{max} = \frac{1}{N}\max_{n}\left\{\frac{1}{N}\left|\sum_{k=0}^{N-1}\left|\hat{y}(k)e^{-j2\pi nk/N}\right|\right|^{2}\right\} \tag{22}$$

where $\hat{y}(k)$ is magnitude normalized complex envelope.

A discrimination capability for binary phase and Costas codes can be obtained to separate them from the rest of the pulse modulation schemes. Invariance is achieve by $1/N^2$ normalization with respect to the data sequence length.

The second feature is the maximum of the PSD of the squared complex envelope. In this case, $\tilde{y}(k)$ is replaced with $\hat{y}^2(k)$ due to the fact that the squared complex envelope is constant for binary phase signals.

4.8 Instantaneous Signal Features

The radar signals instantaneous properties are very distinctive for frequency and phase modulations. First, two features based on the direct estimate of the instantaneous phase (i.e., the phase of the complex envelope) are given. Note that these features are as defined by Azzouz and Nandi[4]:

1) Standard deviation of the absolute value of the instantaneous phase

$$\widehat{\sigma_{\phi}} = \sqrt{\frac{1}{N}\left(\sum_{k}\phi^{2}(k)\right) - \left(\frac{1}{N}\sum_{k}|\phi(k)|\right)^{2}} \tag{23}$$

   where $\phi(k)$ is the defined between $-\pi$ and $\pi. N$ is the number of nonweak samples contributing to the summation (i.e., samples whose amplitude is larger than some predefined threshold). The employed threshold was 0.2 of the maximum amplitude.

2) Standard deviation of the absolute value of the normalized centered instantaneous frequency

$$\widehat{\sigma_f} = \sqrt{\frac{1}{N}\left(\sum_k \tilde{f}^2(k)\right) - \left(\frac{1}{N}\sum_k \left|\tilde{f}(k)\right|\right)^2} \tag{24}$$

where $\tilde{f}(k)$ is the normalized centered instantaneous frequency, that is,

$$\tilde{f}(k) = \frac{\left(f(k) - \mu_f\right)}{max\left|f(k) - \mu_f\right|} \tag{25}$$

where $f(k)$ is the instantaneous frequency and μ_f is the mean of $f(k)$. The sums are again taken over nonweak samples with the same threshold.[5]

5. Statistics

Statistical processing of the radar data provides statistical techniques/methodology to condense the radar data in quantitative terms. Reduction of the measured radar data provides a mechanism for the interpretation of the data. These statistical definitions are described in the following subsections.

5.1 Mean

Mean is the most common measure of a statistical distribution. In this case, mean is arithmetic average for a set of measurements:

$$\overline{\boldsymbol{x}} = \mu = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{x}_i. \tag{26}$$

5.2 Variance

Variance is a measure of the dispersion of a waveform about its mean, called the second moment of the measurements:

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (\boldsymbol{x}_i - \overline{\boldsymbol{x}})^2 \tag{27}$$

5.3 Standard Deviation

Standard deviation is a measure of the variation of a set of data values. Standard deviation is defined as the square root of the variance moment:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\boldsymbol{x}_i - \overline{\boldsymbol{x}})^2} \tag{28}$$

5.4 Kurtosis

Kurtosis is a measure of the tails of the statistical distribution. This provides a description of the outliers in the distributions:

$$\kappa = \frac{\sum_{i=1}^{N}(\boldsymbol{x}_i - \bar{\mu})^4}{N\sigma^4} \tag{29}$$

6. Higher-Order Statistics

HOS advance the fundamental mathematical statistics to provide additional features to compare radar measurements. These higher-order features are moments beyond the variance and kurtosis. Use of the HOS provides additional information about the shape of the data.

6.1 Moments

The definition for moments are defined as follows:

$$\mathrm{M_p} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}}(\mathrm{x_i} - \overline{\mathrm{x}})^{\mathrm{p}} \tag{30}$$

where p is the order of the moment, N is the number of data samples, i is the index of the data sample, and x¯is the mean value of the data set.

Moments are simply the expectation (or mean) of the variable data raised to the power by the order of the moment.

6.2 Cumulants

Cumulants are alternative method to summarize the distribution of a data set. Cumulants are related to the moments the natural logarithm of the characteristic function. Let characteristic function and second characteristic function, respectively, as

$$\Phi(s) = \int_{\infty}^{-\infty} f(x)e^{sx}dx \tag{31}$$

and

$$\Psi(s) = \ln\Phi(s) \tag{32}$$

The nth-order cumulant of x is defined as the nth derivative of the second characteristic function evaluated at $s = 0$:

$$\lambda_n = \frac{d^n\Psi(0)}{ds^n} \tag{33}$$

The computation of these cumulants can be mathematically determined as a function of equal and lower-ordered moment, which provides for an easier numerical calculation

6.3 Notation

The radar signal is represented by in a complex format. For the calculation of the moments, the moment generation is modified to incorporate a conjugate term. In this case, the moment notation is defined as

$$M_{x,a,b} = E\left[x^a(\bar{x})^b\right], a, b \in \mathbb{Z}^+ \tag{34}$$

where E is the expectation operator or mean calculation, x is the variable, and $\bar{x}$ is its complex conjugate. The order of this moment is $a + b$.

The cumulant is denoted with following notation: $C_{x,a,b}$. Instead of explicitly calculating statistical moments, they can be numerically expressed as combination of moments of comparable or lower orders.

6.4 Normalization

One potential problem in using these statistics as they are is that the magnitude of the cumulants increases with their order. This characteristic could have the unintended consequence of weighting these larger statistics more heavily in the classification scheme. To mitigate this effect, Geisinger proposed raising each cumulant to the power $\frac{2}{n}$, where n is the cumulant's order. Simulations showed that taking the magnitude of the statistics and normalizing the cumulants according to their order greatly improved the discrimination power of the features considered when dealing with noise. However, simulations also showed that some of the statistics were very sensitive to the received signal power. This characteristic could have the unintended consequence of weighting these larger statistics more heavily in the classification scheme.[6]

Normalization involves no loss of information and achieves two important goals. The first is that the power level of the signal appears linearly in the various cumulant calculations. The second is that the higher-order cumulants are not emphasized over the lower-order cumulants.[7]

6.5 Modulation Classification with HOS of LPI Radar

Raghu et al.[8] evaluated the use of HOS techniques to identify certain LPI radar signatures. When the signals are in a noisy environment or under low SNR, it may be very difficult to detect them. Detection of the LPI signal is possible with Wigner–Ville time-frequency processing, but the identification of the modulation is not possible since the phase information is not preserved in the processing technique. LPI radar signals use phase modulation to reduce their detectability. The modulation used in this study were Barker, P1, P2, P3, and P4 codes. Barker signals use two-phase combination, while the P1, P2, P3, and P4 are different polyphase coded signals. The authors used a bispectrum image to identify these modulations. A bispectrum image are created by a process that uses dual fast Fourier transform (FFT) with sliding window size over the input signature. Identification of the modulation are based on operator image recognition.

6.6 Modulation Classification with HOS and Wavelet Packet Transform

The detection and localization of the radar pulse under low SNR conditions are important to radar operation. A purposed technique that employs wavelet packet transform with HOS has been evaluated. Wavelet packet transform is similar to time-frequency transform except the correlation is performed on a prescribed shape that changes in amplitude and duration length. After decomposition through the Wavelet packet transform, the noise can be filtered out through a technique known as denoising. In this process, wavelet levels below a certain threshold are basically zeroed out. The inverse of the Wavelet packet transform will yield a filtered signal where the noise has been minimized. A potential problem is that the pulse signal can removed in this process. The authors proposed the use of HOS processing to decide the threshold level. They developed a procedure using the kurtosis estimation to establish an iterative operation to remove the noise.[9]

6.7 Modulation Classification with HOS and Image Processing

The following types of modulation were used in this study: frequency-modulated continuous wave (FMCW), Frank-coded signals, P3 codes, P4 codes, Costas-coded signal, and stepped-frequency codes. The authors evaluated a system composed of a bank of parallel filters. Each filter feeds a third-order cumulant operator and detector. The outputs are used to generate a time-frequency plot. The time-frequency image is converted into a two-level image and image morphology processing techniques are applied to enhance the image shape. Modulation recognition is then based the pattern recognition.[10]

7. Fourier Transform

The Fourier transform is a mathematical transform that decomposes a time-series sequence into a frequency-domain representation in terms of sinusoidal components (i.e., a series of complex frequency components represented by sine and cosine values). The mathematical representation for the Fourier transform and the inverse can be expressed as follows:

$$F\{x(t)\} = X(f) = \int_{-\infty}^{\infty} x(t)\, e^{-i2\pi f t} dt \tag{35}$$

$$F^{-1}\{X(f)\} = x(t) = \int_{-\infty}^{\infty} X(f)\, e^{i2\pi f t} df \tag{36}$$

The Fourier transform is good for stationary signals where the waveform does not change during the sampling time. Time-dependent information is not incorporated into the output response. The Fourier transform output is dependent on the alignment of the input signal onto the transformation spacing. The transition endpoints are critical to the output response. A mismatch at the endpoint will result in leakage. This leakage effect results in what appears as signals appearing across the domain even though the actual signal may be concentrated at a particular frequency. This necessitates the use of windowing functions that are applied to the input signal to reduce the artifact due to leakage.

7.1 Discrete Fourier Transform (DFT)

DFT is basically the discrete representation of the Fourier transform. It converts an equally spaced finite sample sequence into a same-length, frequency-domain representation. It can be expressed as follows:

$$F\{x(i)\} = X[k] = \sum_{k=0}^{N-1} x(i)e^{-j\frac{2\pi}{N}ik} \ (i = 0, \dots, N-1) \tag{37}$$

$$F^{-1}\{X[k]\} = x[i] = \frac{1}{N}\sum_{k=0}^{N-1} X[k]e^{j\frac{2\pi}{N}ik}, (i = 0, \dots, N-1) \tag{38}$$

7.2 FFT

FFT is a mathematical algorithm that reduces the number of numerical computations necessary for the computation of the DFT. Size of the FFT output is limited to the base power of 2. The algorithm reduces the computational load factor for calculation for points N from $2N^2$ to $2NlogN$. The output of the FFT is only available after it has been calculated for the entire frequency-domain representation versus the DFT, where it is faster only if the output for one particular frequency is needed.

8. Time-Frequency Transforms

As stated for the Fourier transform, the frequency-domain representation is good for stationary signals where the waveform does not change during the sampling time. To capture conditions where the signal is changing during the sampling window, the signal can be divided into smaller frame size and a series of Fourier transforms calculated for each frame. There are different forms of this time-frequency transform as expressed in the following sections.

8.1 Short-Time Fourier Transform (STFT)

STFT is generated by using the DFT on a smaller frame length than the origin data frame of length n. A partitioning of the origin data frame into "m" DFT computation can be expressed as

$$X_{STFT}[m, n] = \sum_{k=m}^{m+L-1} x[k]g[k-m]e^{-j2\pi n(k-m)/L} \tag{39}$$

where x[k]is the signal and g[k]is a rectangular window function of length L

Each DFT output is used to form a complex representation of the signal where "m" is used to provide a temporal indicator. Note that the frequency resolution is not as fine as a DFT performed on the entire data sequence.

8.2 Cohen

The Cohen transformation describes a general class of time-frequency transformation obtained through a quadratic formulation with a smoothing kernel applied to reduce interference terms created in the mathematical operation. The Cohen transformation is expressed as

$$C_{x,x}^{\phi}(t,f) = \iiint \phi(\xi,\tau)e^{j2\pi\xi(s-t)}x\left(s+\frac{\tau}{2}\right)x^{*}\left(s-\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\xi ds d\tau \quad (40)$$

where $\phi(\xi,\tau)$ is the kernel of the distribution.

8.3 Wigner–Ville

The Wigner–Ville transformation is a time-frequency transformation that overcomes the stationary requirement of the Fourier transform to be applicable to nonstationary features. A mathematical expression for Wigner–Ville is as follows:

$$WV_{x,x}(t,f) = \int_{-\infty}^{\infty} x\left(t+\frac{\tau}{2}\right)x^{*}\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\tau \quad (41)$$

8.4 Choi–Williams

The Choi–Williams transformation is a time-frequency transformation of the Cohen class time-frequency transformation. A kernel function filters the cross-terms products that differ in both time and frequency center. The Choi–Williams transformation is defined as follows:

$$CW_{x,x}(t,f) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} e^{(-\alpha(\eta\tau)^2)}A_x(\eta,\tau)\,e^{j2\pi(\eta t-\tau f)}d\eta d\tau \quad (42)$$

where

$$A_x(\eta,\tau) = \int_{-\infty}^{\infty} x\left(t+\frac{\tau}{2}\right)x^{*}\left(t-\frac{\tau}{2}\right)e^{-j2\pi t\eta}dt \quad (43)$$

8.5 Image Processing: Morphological Feature Extraction

Morphology is a set of image processing techniques that use shapes to modify the image characteristic. These operations apply a structuring element to an input image, creating an output image value of each pixel based on neighborhood pixel values. Fundamental operations are known as dilation and erosion. Dilation corresponds to opening or expanding the boundaries of the image object, while erosion performs the opposite in reducing or shrinking the image shape. These image operations are applied with structuring elements and rules associated with the desired function. Morphological operations rely only on the relative ordering of pixel values, not on their pixel numerical value.[22]

Binarization of images is the process of converting an image into a binary or two-state pixel image. This is computed through conversion of the image based on a simple threshold. Although this may reduce complexity, there is a high probability that artifacts may be generated and distort the desired shape. The morphological operations are applied to clean the image.

8.6 Automated Classification with Choi–Williams Distribution Extraction Integrated with Neural Networks

Zilberman et al.[11] developed an automated modulation classification process that used the time frequency: the Choi–Williams distribution. This particular time-frequency processing was chosen due to the minimization of the cross-term products when compared to a Wigner–Ville distribution. Feature extraction was generated from the time-frequency image through the use of image processing techniques (morphological operations) using various shape kernels. Through a series of erosion, dilation, and adaptive threshold binarization, the image is simplified to produce an image of the modulation energy centroid. Classification is performed using a multilayer perceptron (MLP) neural network. Using computer simulation, the algorithm was evaluated against binary phase-shift keying (BPSK), FMCW, Frank, P4, and polyphase modulation.

8.7 Automated Classification with Choi–Williams Distribution, Standard Signal Extraction Feeding a Dual Elman Neural Network Classifier

Zhang et al.[12] provided a detailed roadmap of the process that was employed in their modulation classification algorithm. An automatic modulation recognition algorithm was the primary goal. Choi–Williams time-frequency processing was selected as one of the primary techniques to transform the radar time signature (i.e., to automate the feature extraction from the time-frequency image). The time-frequency image was simplified into a binary image using techniques outlined in their paper. Through morphological operations, such as erosion and dilation, binary image shape features were isolated and enhanced. Features were extracted from the image through the statistical image moments called pseudo-Zernike moments.

In addition to the Choi–Williams processing, the authors used other signal processing on the radar signature in order to have features for classification. A list of features is included in their report. Some of these features were instantaneous frequency and phase; statistical features like standard deviations, moments, and cumulants; and PSD features. A total of 23 features were used in their classification algorithm.

The authors used a neural network called Elman neural network (ENN). An ENN network incorporate a feedback path in the network that is typical feedforward only. In the classification algorithm, there are actually two ENNs used in parallel. Network 1 is used to classify linear frequency modulation (LFM), Costas, and binary phase modulations. Network 2 is used on the polyphase modulation signals. Their algorithm was evaluated against the following modulations: LFM, Costas, binary, Frank, P1, P2, P3, and P4.[12]

9. Cyclostationary

HOS are defined as the nth-order moments or cumulants (nonlinear combination of moments) of random signals. In the frequency domain, they correspond to HOS (also known as polyspectra), which are, by definition, multidimensional Fourier transforms of HOS (moments or cumulants). Particular cases of higher-order spectra are the third-order spectrum called the bispectrum and the fourth-order spectrum, called trispectrum, which are the Fourier transforms of the third- and fourth-order statistics adequately. Thus, the power spectrum is a part of the class of higher-order spectra (i.e., it is a second-order spectrum). The power spectrum or PSD and auto-correlation function provide very useful information in the design and analysis of the linear predictive systems.

9.1 Cyclostationary Processing of LPI Radar Signals

The researcher, Antonio F Lima, focused his thesis work[13] on using cyclostationary processing on LPI signatures. He studied the use of cyclostationary properties against the following LPI signals: FMCW, Frank, P1, P2, P3, P4, and Costas modulation. These types of modulation have certain periodicity that can be exploited when the spectral correlation are performed. Two implementations of cyclostationary processing were implemented in MATLAB and attached in the thesis appendix: FFT accumulation method (FAM) and the direct frequency-smoothing method (DFSM). Certain modulation parameters can be interpreted/ extracted from the cyclostationary image that results from the cyclostationary processing technique. Modulation classification is unique to the modulations, but it would require image recognition on the part of the viewer.

9.2 Maximum a Posteriori (MAP) Classifier for Communication and Radar Signals Using Features Based on Cyclostationary and Cumulants

Hadjis' thesis work[14] involved the development of a MAP classifier based on features that are derived from estimated duty cycle, cyclic spectral correlation, and cyclic cumulants. In his work, he studied various modulations associated with communication system as well as radar systems. The following modulations were evaluated: BPSK, quadrature phase-shift keying (QPSK), 16-quadrature amplitude modulation (QAM), 64-QAM, 8-phase-shift keying (PSK), and 16-PSK communication modulations, as well as Barker$_5$-, Barker$_{11}$-, Barker$_{5,11}$-, Frank$_{49}$-, Px$_{49}$-, and LFM modulations for radar modulations.

The author generated a feature list based on the previously mentioned signal processing techniques. A feature vector of 25 classification features was derived from the application of cyclostationary- and cumulant-based processing. Using simulations, a features-based classifier was trained and evaluated under various SNR levels and pulse parameters. The classifier features and their equations are listed in Table 1.[14]

Table 1. Classifier feature equations

Feature	Equation	Eq. No.
ψ_1	$\left(\frac{S_{X_T}^{2*fc}(n,0)_{\Delta f}}{S_{X_T}(n,f_C)_{\Delta f,Adj}}\right)_{N'=328}^{N=4096}$	(44)
ψ_2	$\left(\frac{MAX_f(S_{X_T}^{2*fc}(n,f)_{\Delta f}))}{MAX_f(S_{X_T}(n,f)_{\Delta f,Adj})}\right)_{N'=328}^{N=4096}$	(45)
ψ_3	$\left(\frac{S_{X_T}^{2*fc}(n,0)_{\Delta f}}{S_{X_T}(n,f_C)_{\Delta f,Adj}}\right)_{N'=36}^{N=4096}$	(46)
ψ_4	$\left(\frac{MAX_f(S_{X_T}^{2*fc}(n,f)_{\Delta f}))}{MAX_f(S_{X_T}(n,f)_{\Delta f,Adj})}\right)_{N'=36}^{N=4096}$	(47)

Table 1. Classifier feature equations (continued)

Feature	Equation	Eq. No.
ψ_5	$\hat{\delta}_C = \dfrac{P_{avg}}{\hat{P}_0}$	(48)
ψ_6	$\left\lvert C_{2,1}^{\beta=0} \right\rvert$	(49)
ψ_7	$\left\lvert C_{4,0}^{\beta=4f_C} \right\rvert$	(50)
ψ_8	$\left\lvert C_{8,0}^{\beta=8f_C} \right\rvert$	(51)
ψ_9	$\dfrac{\left\lvert C_{4,2}^{\beta=0} \right\rvert}{\left\lvert C_{2,1}^{\beta=0} \right\rvert^2}$	(52)
ψ_{10}	$\dfrac{\left\lvert C_{4,0}^{\beta=4f_C} \right\rvert}{\left\lvert C_{2,1}^{\beta=0} \right\rvert^2}$	(53)
ψ_{11}	$\dfrac{\sqrt[3]{\left\lvert C_{6,1}^{\beta=4f_C} \right\rvert}}{\left\lvert C_{2,1}^{\beta=0} \right\rvert}$	(54)
ψ_{12}	$\dfrac{\sqrt[3]{\left\lvert C_{6,1}^{\beta=4f_C} \right\rvert}}{\left\lvert C_{4,0}^{\beta=4f_C} \right\rvert}$	(55)
ψ_{13}	$\dfrac{\sqrt[3]{\left\lvert C_{6,3}^{\beta=0} \right\rvert}}{\left\lvert C_{2,1}^{\beta=0} \right\rvert}$	(56)
ψ_{14}	$\dfrac{\sqrt[3]{\left\lvert C_{6,3}^{\beta=0} \right\rvert}}{\left\lvert C_{4,0}^{\beta=4f_C} \right\rvert}$	(57)
ψ_{15}	$\dfrac{\sqrt[4]{\left\lvert C_{8,0}^{\beta=8f_C} \right\rvert}}{\left\lvert C_{2,1}^{\beta=0} \right\rvert}$	(58)

Table 1. Classifier feature equations (continued)

Feature	Equation	Eq. No.
ψ_{16}	$\dfrac{\sqrt[4]{\left\lvert C_{8,0}^{\beta=8f_C}\right\rvert}}{\sqrt{\left\lvert C_{4,0}^{\beta=4f_C}\right\rvert}}$	(59)
ψ_{17}	$\dfrac{\sqrt[4]{C_{8,0}^{\beta=8f_C}}}{\sqrt[3]{\left\lvert C_{6,3}^{\beta=0}\right\rvert}}$	(60)
ψ_{18}	$\dfrac{\sqrt[4]{\left\lvert C_{8,2}^{\beta=8f_C}\right\rvert}}{\left\lvert C_{2,1}^{\beta=0}\right\rvert}$	(61)
ψ_{19}	$\dfrac{\sqrt[4]{\left\lvert C_{8,2}^{\beta=8f_C}\right\rvert}}{\sqrt{\left\lvert C_{4,0}^{\beta=4f_C}\right\rvert}}$	(62)
ψ_{20}	$\dfrac{\sqrt[4]{C_{8,2}^{\beta=4f_C}}}{\sqrt[3]{\left\lvert C_{6,1}^{\beta=4f_C}\right\rvert}}$	(63)
ψ_{21}	$\dfrac{\sqrt[4]{C_{8,2}^{\beta=4f_C}}}{\sqrt[3]{\left\lvert C_{6,3}^{\beta=0}\right\rvert}}$	(64)
ψ_{22}	$\dfrac{\sqrt[4]{\left\lvert C_{8,4}^{\beta=0}\right\rvert}}{\left\lvert C_{2,1}^{\beta=0}\right\rvert}$	(65)
ψ_{23}	$\dfrac{\sqrt[4]{\left\lvert C_{8,4}^{\beta=0}\right\rvert}}{\sqrt{\left\lvert C_{4,0}^{\beta=4f_C}\right\rvert}}$	(66)

Table 1. Classifier feature equations (continued)

Feature	Equation	Eq. No.
ψ_{24}	$\dfrac{\sqrt[4]{C_{8,4}^{\beta=0}}}{\sqrt[3]{\left\lvert C_{6,1}^{\beta=4f_C}\right\rvert}}$	(67)
ψ_{25}	$\dfrac{\sqrt[4]{C_{8,4}^{\beta=0}}}{\sqrt[3]{\left\lvert C_{6,3}^{\beta=0}\right\rvert}}$	(68)

10. Artificial Neural Networks

Artificial intelligence is not a new concept, but has been studied in academia for a long time. One of the areas of interest is called artificial neural networks, where attempts are being made to model the processing power of the human brain. However, such approaches have only recently become practical due to advancements in massively parallel multiprocessor chips, graphical processing units (GPUs), and software tools. The foundation had been laid out through decades of research, but the application was not readily practical until recently.

In the classification of radar signals, the training of neural networks requires lots of labeled or known configuration data that represent the different types of radar signals (modulation) and under different SNRs and other effects, multipath, and fading. Configurations that represent various PWs, PRIs, operating frequencies, pulse shapes, bandwidths, and modulations. Differences between scanning and tracking and detection operations are also important. Simulations can be performed, but actual measurements should be done to adjust the detection and classification performance.

10.1 Multilayer Perceptron (MLP)

MLP is a class of artificial neural network. In neural networks, the processing attempts to produce a decision statistic formed through a combination of simplified, parallel calculations. These neural networks have evolved into various forms/ structures. At a fundamental level, the structure comprises three layers: input, hidden, and output. The input layer is composed of features that provide summary representation of the input data set. With the application of weighting factors to the input nodes, the hidden layer provides a summation of the input nodes and performs an activation function or decision threshold on the hidden node. Finally, the output layer combines the hidden nodes through another set of weights to generate the output decision statistic.

10.2 Convolutional Neural Network

A CNN is a neural network that uses an image as the input layer. The network generates a set of features based on the application of a convolutional calculation on the image. These neural networks have been referred to as deep learning since they leverage many layers of processing before arriving at the output layer.

The CNN has become very powerful and active area of research in the last decade. There is an annual competition, ImageNet, where teams compete on image classification using a large database of labeled images. The level of accomplishment had reached a plateau before Alex Krizhevsky's doctoral work on image recognition at Toronto University. The application of CNN architecture algorithm marked a significant improvement in the ImageNet competition. His algorithm, AlexNet, provided a significant increase in accuracy up to that point in time. He made this code readily available to users, which has helped speed up the development of CNNs.[15]

10.3 Radar Modulation Classification through Dual MLP Networks

Lunden[16] conducted doctoral research in spectrum sensing for communications and radar systems. There has been much research into automatic modulation recognition for communication systems, but a relatively smaller amount as applied to radar systems. Some of the features identified in communications-type modulation have some degree of applicability to radar waveform recognition. There are two basic categories of automatic modulation recognition: likelihood- and feature-based methods. The feature-based methods extract features from the measurement of the signal and decision on the classification is based on the feature values. Lunden's research is concentrated on the feature-based methodology using some standard features. In addition, features are derived from Wigner–Ville and Choi–Williams distributions. Since the application of time frequency only forms an image of the frequency spectrum, he had to apply some image processing techniques in order to extract features.

The following pulse compression modulations were considered: linear frequency modulation, Costas frequency codes, binary codes, Frank, P1, P2, P3, and P4 polyphase codes. A dual, parallel MLP network was developed for radar waveform classification. The following features were evaluated in Lunden's research[16]:

- Time lag of the maximum cross-correlation between pulse and time-reversed pulse
- The Choi–Williams distribution features were the second-, third-, and fourth-order pseudo-Zernike moments. In addition, the features from the binary form of the Choi–Williams distribution: number of objects in image, location of the peak signal, and the standard deviation of the width associated with the objects.
- The Wigner–Ville distribution features were as follows: the standard deviation of the instantaneous frequency, the ratio of the sidelobe, and maximum of the autocorrelation of the instantaneous frequency.
- Standard deviation of the instantaneous phase and frequency. The instantaneous frequency was median-filtered to suppress the spikes caused by the phase changes in the phase-coded signals.
- The bandwidth feature from using a symbol-rate-sampled signal.
- The difference between the beginning and ending phases of the pulse.
- PSD-based features: symmetry, the maximum of the PSD, and the maximum of the PSD of the squared signal.
- Zero-lag moments of the complex envelope. Moments up to eighth order without any complex conjugated components.
- Zero-lag cumulants of the complex envelope. Second- to sixth-order cumulants were used.

10.4 Radar Modulation Classification through CNN with Choi–Williams Distribution

Zang et al.[17] provided a process for developing radar modulation classification through the incorporation of several processing techniques. The following modulations were simulated and evaluated through the proposed algorithm: Barker, LFM, Costas, Frank, T1, T2, T3, and T4 modulation codes. A Choi–Williams image was selected as the basis for input signal processing. Standard image processing techniques such as image denoising and binarization processing were performed to simplify and enhance shape recognition. The CNN architecture is typically a very deep configuration, meaning that it has many intermediate layers between input and output. The proposed architectural network is a modification of the CNN configuration in which a MLP network is added as the final classifier. In the CNN layer, a feature vector is created to feed the MLP network and provides a reduction in the typical depth of a CCN architecture.

10.5 Radar Modulation Classification through CNN with Wigner–Ville Distribution

Wang, et al.[18] explored the use of the Wigner–Ville distribution. Typically, most researchers have rejected this particular time-frequency distribution due to the cross-term products generated in the time-frequency image. Selection of other types of time-frequency distributions have shown that the power spectrum of Gaussian white noise occupies the full-frequency band, thereby Cohen-type distributions do not offer an advantage for the rejection of background noise. An evaluation of the statistical characterization of the time-frequency image showed that cross-term products and noise could be separated from the desired signal. The CNN network was used as a classifier in their architectural algorithm. A naïve filter was incorporated into the CNN processing where the averaging technique is performed on the CNN processing block to minimize the cross-term products and noise terms. The system was evaluated against eight modulations: Barker, LFM, Costas codes, Frank, and T1, T2, T3, and T4 polyphase codes.

10.6 Radar Modulation Classification through Cohen Class Time-Frequency Processing with CNN Classification

Qu et al.[19] introduced a new kernel to Cohen class time-frequency image processing with CNN classification. Twelve kinds of modulation signals were used in this evaluation: LFM, sinusoidal frequency modulation (SFM), 2-FSK, 4-FSK, dual frequency modulation (DLFM), even quadratic frequency modulation (EQFM), multiple linear frequency modulation (MLFM), BPSK, Frank, MP, and composite modulation (LFM-BPSK, 2FSK-BPSK).

Typically, Choi–Williams time-frequency processing is used by researchers as input into the CNN. In this work, the authors have introduced a new type of Cohen-type time-frequency kernel used in the image processing that have a higher noise rejection. The general form of the Cohen time-frequency computation is

$$C(t,\omega) = \frac{1}{4\pi^2}\iint AF(\tau,v)\phi(\tau,v)e^{-vt-j\omega\tau}dvd\tau \tag{69}$$

$$AF(\tau,v) = \int x\left(u+\frac{\tau}{2}\right)x^*\left(u-\frac{\tau}{2}\right)e^{jvu}du \tag{70}$$

The authors have suggested that a good kernel that might be used is a Gaussian kernel expressed as

$$\phi(\tau, v) = exp\left[-\frac{(\tau v)^2}{\sigma}\right] \tag{71}$$

For radar signals, this particular kernel is not good choice, since it does not reduce the artifacts for radar signals. The authors have proposed a new kernel as follows:

$$\phi(\tau, v) = e^{-(\alpha\tau^2+\beta v^2)} \tag{72}$$

where α and β are parameters that adjust the shape of the kernel function.

The estimate for α and β is four times the standard difference of the Gaussian function.

The time-frequency image is processed through a series of image processing techniques that incorporate a 2-D Wiener filtering, morphological feature extraction, and binarization to enhance the image prior to application to CNN classification. Otsu's method is used in the binarization process to determine the optimum threshold level for the conversion process. LeNet-5 was the CNN architectural form used in the classification. The authors had increased the layers in this configuration and modified the parameters to improve the classification performance to a –6 dB SNR level.[19]

10.7 Radar Modulation Classification LPI Radar Waveform Recognition Technique (LWRT) with CNN Classification

Kong et al.[20] examined LWRT, which is a popular technique that is a combination of the time-frequency transformation and the CNN network for modulation classification. A total of 12 types of modulations were evaluated as follows: LFM, Costas, BPSK, Frank, P1, P2, P3, P4, T1, T2, T3, and T4.

Detection and classification of LPI radar signals are very difficult under low SNR conditions. In the authors' algorithm, they implemented a filtering technique used in GPS to enhance the quality of the signal. The intra-pulse signature is defined as

$$y[k] = x[k] + w[k] \tag{73}$$

where x[k]is the discrete time complex LPI samples and w[k]is the complex Gaussian white noise.

This signature sequence was averaged over N_a consecutive samples of $y[k]$ and defined as

$$y_a = \frac{1}{N_a} \sum_{k=0}^{N_a - 1} y[k + nN_a] \tag{74}$$

where

$$N_a = \frac{N_1}{N_{SC}} \tag{75}$$

and

$$N_1 = \frac{f_s}{f_{max}} \tag{76}$$

where f_max is the maximum frequency allowed by the receiver bandpass filter and f_s is the sampling frequency.

This filtered signal is used by the Choi–Williams distribution to generate a time-frequency image of the modulated signal. The time-frequency images for the 12 modulations have distinct feature shapes. These feature objects varies in terms of the number of distinct objects, pattern of the objects, and symmetry as a function of time in the image. In this case, the time frequency has less resolution or fewer details when compared to having the original sampled waveform that is fed directly into the Choi–Williams distribution. To compensate, the authors reimaged the time-frequency image through a series operations consisting of cropping and resizing of the image. Then the authors evaluated the hyperparameters of the CNN, such as the input size, number of filters, filter size, and number of neurons to select the hyperparameters would provide the best classification under various SNR conditions.[20]

10.8 Radar Modulation Classification CNN in Conjunction with Tree Structure Classifier

Wan et al.[21] have developed a radar modulation classification using the Choi–Williams distribution and CNN network as a feature generation operation. Instead of using the CNN as the classifier, the authors used a final layer of the CNN as feature vector for a tree structure-based machine learning process optimization (TPOT) classifier. The 12 radar modulation evaluated were as follows: Barker, LFM, Costas, T1, T2, T3, T4, Frank, P1, P2, P3, and P4.

The process of using the Choi–Williams distribution and CNN follows the standard procedure. Radar signatures are transformed into a time-frequency image and a binarization operation is used to simplify the image for the CNN processing. The authors provided detailed steps to their binarization operation in their paper.

Typically, the CNN configuration is used as the classifier for modulation recognition, but the CNN output was not used in the final classification in this algorithm. The last layer of the CCN network was extracted to form the feature vector for modulation recognition. In this case, the use of the Choi–Williams distribution and CNN were used as a training process to learn and provide the initial learning features.

The authors have extracted the fully connected layer of the CNN as input to combination of classifiers. The classifier algorithm was labeled as a TPOT classifier. The CNN data features are sent to the TPOT to select and optimize the classifier parameters. The TPOT is optimized through the use of various machine learning algorithms. A technique called "genetic programming" is used to optimize the feature vector as initially generated by the CCN training. The TPOT classifier is constructed as tree structure decision to select the among various machine learning classifiers: decision tree, random forest, support vector machine (SVM), logistic regression, and KNN.[21]

11. Summary and Conclusions

In this report, we described various techniques for radar pulse modulation classification. Recognition of the radar pulse modulation shares similar concepts of modulation recognition for communications systems. For most of the survey papers and reports, the assumption is that the radar signature operates in an isolated environment without inference except for white Gaussian noise. Also, the assumption is made that the radar pulse can be detected and the intra-pulse signature can be extracted for some of the classification techniques.

SEI was the work conducted in radar identification through physical radar measurements such as operating frequency, PRI, and PW. Initially, signal processing capability was very limited and radar identification related to these measurements was dependent on the capabilities/interpretation of the radar/signal operator. LPI radar evolved to minimize the detectability of these radar systems, therefore, making manual operation extremely difficult. Luckily, technology advancement has also produced capabilities to automatically detect and classify these LPI modulations.

Modulation classification capabilities are being achieved through the application from many areas of engineering, mathematics, statistics, digital signal processing, image processing, pattern recognition, machine learning, and artificial neural networks. Some of the techniques have evolved over many decades ago, but only recently have the hardware capabilities advanced to the point that the processing is closer to the real time domain.

Classification of the radar modulation can divided into two general groups: feature based and image based. Radar pulse modulations use the complex representation of the radar signature (i.e., in phase and quadrature [I/Q] representation). The instantaneous frequency and phase are two important elements that can be formulated from the I/Q signal. For featured-based classification, the information for classification is extracted from the intra-pulse measurement. Features are derived through statistical transformation of the I/Q signal. Various machine learning techniques can be applied to statistical features to determine the modulation class.

Modulation classification can also be based on pattern recognition that uses time-frequency transforms, image processing, and artificial neural networks. In this case, there is no need to perform feature extraction as a preliminary step in the classification process. There are various time-frequency transforms that have been investigated. The output of the time-frequency transforms provide an image basis for the classification process. In the majority of the researched investigations, the CNN was the classifier of choice. Features are automatically formulated in the CNN through an extensive training process. This training process requires a significant amount of labeled data. Computer simulations were the main process in the evaluation of the modulation algorithms. Computer simulations provide a good initial step, but evaluations need to incorporate real-world measurements.

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List of Symbols, Abbreviations, and Acronyms

ARL	Army Research Laboratory
BPSK	binary phase shift keying
CCDC	Combat Capabilities Development Command
CNN	convolutional neural network
DOA	direction of arrival
DBN	deep belief network
DFSM	direct frequency-smoothing method
DFT	discrete Fourier transform
DLFM	dual frequency modulation
ENN	Elman neural network
EQFM	even quadratic frequency modulation
FAM	FFT accumulation method
FMCW	frequency modulated continuous wave
FFT	fast Fourier transform
FMOP	frequency modulation on pulse
FSK	frequency shift keying
GPS	global positioning system
GPU	graphical processing unit
HOS	high-order statistics
I/Q	in phase and quadrature
KNN	k-nearest neighbor
KLT	Karhunen–Loève transformation
LDA	linear discriminant analysis
LFM	linear frequency modulation
LPI	low power intercept

LWRT	LPI radar waveform recognition technique
MAP	maximum a posteriori
MLP	multilayer perceptron
MLFM	multiple linear frequency modulation
PRI	pulse repetition interval
PW	pulse width
PSD	power spectral density
PSK	phase-shift keying
QAM	quadrature amplitude modulation
QPSK	quadrature phase-shift keying
radar	radio detection and ranging
RF	radio frequency
SEI	specific emitter identification
SFM	sinusoidal frequency modulation
SNR	signal-to-noise ratio
STFT	short time Fourier transform
SVM	support vector machine
TOA	time of arrival
TPOT	tree structure-based machine-learning process optimization
UMOP	unintentional modulations on pulse

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