Classification of Radar and Communications Signals using Wideband Autonomous Cognitive Radios

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***Abstract*—Spectrum awareness is one of the most challenging problems in wideband autonomous cognitive radio (WACR) design. Detection and classification of low-SNR signals is important for proper WACR functionality as it enables the radio to adapt to the user needs and surrounding RF environment. In this context, identification of radar and communications signals is critical in various applications, especially, electronic warfare. This paper introduces a classification framework for radar and communications signals based on their cyclostationary features, specifically, the cyclic profile. Two classification algorithms are used: an artificial neural network (ANN) and a convolutional neural network (CNN). The simulation results show that cyclic profile is a good candidate compared with other features to distinguish between radar and communications signals even at very low SNRs. Furthermore, from a complexity perspective, the ANN is shown to be more effective than the CNN in the proposed classification framework.**

***Index Terms*—Convolutional neural network, cyclostationary features, pulsed radar, signal classification, spectrum awareness, wideband autonomous cognitive radios.**

I. INTRODUCTION

With their ability of self learning and autonomously reconfiguring a complex RF system, wideband autonomous cognitive radios (WACRs), have found increasing relevance in a wide range of applications during the past few years including, for example, military, homeland security, aerospace and consumer wireless communications [1], [2]. Indeed, the key to such autonomous operation is the spectrum awareness. Unlike traditional RF systems that treat each detected signal equally and pass it through the same processing steps, WACRs may distinguish among different signals to determine what is important and what is not. As an example, a GPS spoofing signal or unmanned aerial vehicle (UAV) command link may be present in a band where only radars are expected. In this case, the WACR may need to identify and isolate these unexpected signals.

The purpose of this paper is to distinguish between radar and communications signals. We selected these two types of signals because they are widely used and they may overlap in various applications. For example, in modern electronic warfare, integrative reconnaissance technology for radar and communication signals on a single platform can be found [3]. However, the proposed approach can be extended to beyond radar and communications signals to detect, characterize and label all different types of signals, such as, military, GPS, space operations. Furthermore, a second level of classification could be applied to each type of these signals: For example, the communications signals could be classified to WiFi, Bluetooth, LTE, etc.

Despite the importance of radar and communications signals, discrimination between these two classes of signals still remains relatively unexplored. Most of the work on this area are done separately for classification of communications or radar signals, and not both together [4] – [6]. For example, in [4], different communications signals are considered: global system for mobile communications (GSM), digital enhanced cordless telephony (DECT), radio local area network (RLAN), digital audio broadcasting (DAB) and digital video broadcasting terrestrial (DVB-T). The channel bandwidth in [4] was found to be the most discriminating parameter and it is used as a reference feature. For classification, a radial basis function (RBF) neural network is employed.

The authors in [5] introduced a discriminating mechanism between two modes (FH-CDMA and DS-CDMA) related to two standards (Bluetooth and IEEE 802.11b) in an indoor environment. The standard deviation of the instantaneous frequency and the maximum duration of a signal were extracted using time-frequency analysis in [5] and neural networks were used for identification of active transmissions using these features. On the other hand, a system for automatically recognizing radar waveforms was introduced in [6]. Eight different radar pulse compression waveforms were considered in [6]: linear frequency modulation (LFM), discrete frequency codes (Costas codes), binary phase codes, Frank, P1, P2, P3, and P4 polyphase codes. In addition, two classifier structures based on the early-stop committee (ESC) and the Bayesian multilayer perceptron (MLP) have been proposed.

Our proposed framework for radar and communications signals classification uses a cyclostationarity based feature known as the cyclic profile. An interesting point of this work is that we selected two communications signals that are widely used: WiFi and LTE, and experimented in separating them versus wide range of different radar signals. The selected radar signals include: LFM pulse, biphase-coded pulse, Barker-coded pulse and Frank-coded pulse. Another aspect of this work is that we investigate the application of deep learning techniques, such as, convolutional neural network (CNN) for radar and communications signals classification. In addition, the artificial neural network (ANN) is used as a traditional classification option for comparison purpose. Furthermore, the

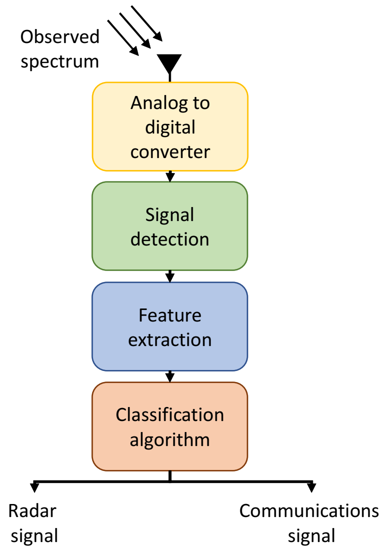

Figure 1. Overview of the proposed cognitive classification framework.

robustness of the proposed technique is tested against white Gaussian noise with different signal-to-noise-ratio (SNR) values.

The remainder of the paper is structured as follows: First, the proposed cognitive classification framework is described in Section II. Section III introduces a case study for a selection of radar and communications signals. The simulation results are presented in Section IV. Finally, concluding remarks are given in Section V.

II. Proposed cognitive classification framework

Figure 1 shows the proposed cognitive classification framework for radar and communications signals. The WACR has to sense the spectrum of interest to detect the presence of the signals. Next, it has to extract features from the detected signals and then use a classifier to identify whether the observed signal belongs to a radar or a communications system.

A. Feature extraction

A good feature set should reduce the data size, and maintain the necessary information to accurately discriminate among the different signals types. The occupied bandwidth and maximum power spectral density are two basic features that are widely used for signal classification. However, if the signals occupy the same bandwidth or have the same power level the classification operation would be very difficult using these features. In this case, cyclostationarity based features may be a good candidate.

Man-made signals such as wireless communication and radar signals typically exhibit cyclostationarity at multiple cyclic frequencies that may be related to the carrier frequency, duty cycle, symbol, chip and code rates, as well as their harmonics, sums, and differences [7]. Exploiting these periodicities allows designing powerful feature detectors with very appealing properties.

A signal $y(t)$ is said to be wide-sense cyclostationary with period T_0 if its mean and autocorrelation are both periodic with period T_0,

$$\mu_y(t+T_0)=\mu_y(t), \qquad R_y(t+T_0,\tau)=R_y(t,\tau). \quad (1)$$

The autocorrelation function of a wide-sense cyclostationary signal can be expressed in terms of its Fourier series components

$$R_y(t,\tau)=\sum_{\alpha} R_y^{\alpha}(\tau)e^{j2\pi\alpha t}, \quad (2)$$

where α is the cyclic frequency and the Fourier component R_y^{α} represents the cyclic autocorrelation function

$$R_y^{\alpha}(\tau)=\frac{1}{T}\int_{-T/2}^{T/2} R_y(t,\tau)e^{-j2\pi\alpha t}dt. \quad (3)$$

The Fourier transform of the cyclic autocorrelation function is known as spectral correlation function (SCF) and is given by

$$S_y^{\alpha}(f)=\int_{-\infty}^{\infty} R_y^{\alpha}(\tau)e^{-j2\pi f\tau}d\tau, \quad (4)$$

where f is the angular frequency.

The major benefit of spectral correlation is its insensitivity to background noise since correlation measures the temporal correlation of different spectral components, and the spectral components of white noise are completely uncorrelated in time. This fact allows the spectral correlation of a signal to be accurately calculated even at low SNRs. SCF computation, however, requires large amount of data and directly using it as a feature may be computationally too prohibitive. Instead, we can use the cyclic profile given by

$$I(\alpha)=\max_{f}\ S_y^{\alpha}(f) \quad (5)$$

as a feature vector for the signal classification.

B. Classification tools

The classification tools used in this work are: artificial neural networks and convolutional neural networks. The ANN is based on back propagation algorithm which is one of the most widely applied neural network models. The back propagation is used to update the weights and biases of hidden layer neurons of the network. The weights and biases are updated such that they minimize the error of each output neuron based on the output predictions it produces versus the correct a priori outputs we know from the training set [8].

The CNN, on the other hand, is one of the deep learning neural networks that have proven very effective in areas such as image recognition and classification. The CNN takes the input and passes it through a series of convolutional, pooling (downsampling), and fully connected layers [9]. Note that in ANN, every neuron in the network is connected to every neuron in adjacent layers. In the CNN, however, each neuron in the first hidden layer will be connected to a small region of the input neurons and each connection learns a weight [9].

III. CASE STUDY

Consider six different signals, where two of them (Sig1 and Sig2) belong to communications systems and the remaining four (Sig3, Sig4, Sig5 and Sig6) belong to the radar systems. All the processing are done in baseband. Sampling rate of 2 $Msamples/sec$ is used for all signals. The radar signals are all pulse compression waveforms. Sig3, Sig4, Sig5 and Sig6 use LFM, biphase-coded pulse, Barker-coded pulse and Frank-coded pulse, respectively. The pulsed radar transmits electromagnetic (EM) waves during a very short time duration, known as pulse width. During this time, the receiver is isolated from the antenna, so that no received signals can be detected during this time. During the time between transmitted pulses, the receiver is connected to the antenna, allowing it to receive any EM waves (echoes) that may have been reflected from objects in the environment. This listening time plus the pulse width represents one pulsed radar cycle time, normally called the pulse reception interval (PRI) [10]. The number of transmit/receive cycles the radar completes per second is called the pulse repetition frequency (PRF), measured in cycles per second.

In LFM, the waveform sweeps the oscillations across a range of frequencies during the pulse transmission time. The phase-coded waveforms, on the other hand, are composed of concatenated subpulses (or chips) where the phase coding from chip to chip is chosen to elicit a desired main-lobe and side-lobe response. For example, in biphase-coded pulse, the relative phase changes between one of two values, either zero or π radians. The parameters of Sig3 that uses LFM are as follows: pulse width = 80 μsec, sweep bandwidth = 0.5 MHz and PRF= 0.4 $Kcycles/sec$. Sig4, on the other hand, uses biphase-coded pulse with the following parameters: chip width = 1 μsec, number of chips = 50 $chips/pulse$ and PRF = 0.4 $Kcycles$. Unlike biphase-coded waveforms, polyphase-code waveforms like Barker and Frank codes posses more than two phase states [10]. Sig5 uses Barker-coded with chip width of 1 μsec, 13 $chips/pulse$ and PRF of 0.4 $Kcycles$. Sig6, on the other hand, uses Frank-coded with the following parameters: chip width = 1 μsec, number of chips = 4 $chips/pulse$ and PRF = 0.4 $Kcycles$.

For communication signals, we have used WiFi signal and LTE signal as Sig1 and Sig2, respectively. The generated WiFi signal is corresponding to the IEEE 802.11 sub 1 GHz (S1G) format physical layer (PHY) packet [11]. Assuming one transmit antenna, Sig1 uses OFDM modulation with a channel spacing of 2 MHz. Sig2, on the other hand, represents the LTE signal that follows model '1.1' in TS 36.141 3GPP specification [12]. The parameters of the signals are chosen such that Sig3 and Sig2 have a similar bandwidth of 0.55 MHz. On the other hand, Sig4, Sig5, Sig6 and Sig1 have similar bandwidth of 0.87 MHz. Furthermore, all signals have the same power level which makes the classification operation more challenging.

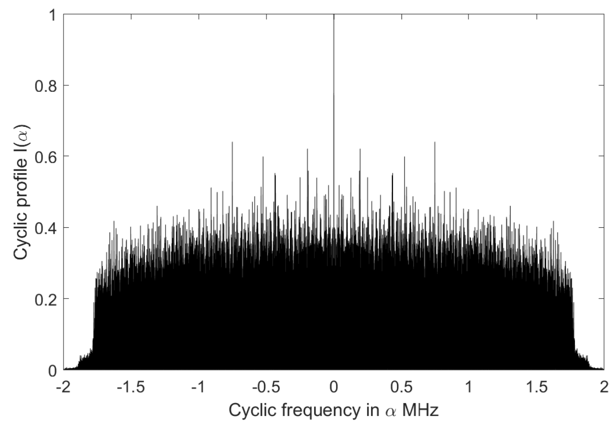

Figure 2. Cyclic profile of normalized SCF for Sig1 (WiFi signal).

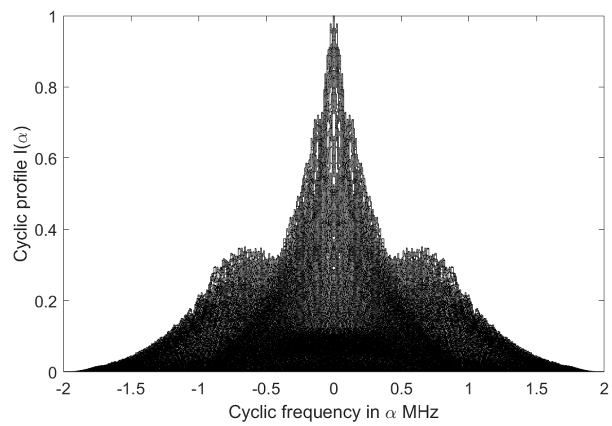

Figure 3. Cyclic profile of normalized SCF for Sig4 (Biphase-coded Pulsed radar signal).

IV. SIMULATION RESULTS

In this section, we conduct four test cases to show the efficiency and the robustness of the proposed cognitive classification technique. In the four test cases, different types of classifiers have been used based on ANN and CNN with different numbers of layers as shown in Table I. For each test case we select four signals for both training and testing from the signals described in the previous section, where the first two signals are communication signals and the other two are radar signals. The target is to classify the signals into two classes: class 1 represents communications signals and class 2 represents radar signals.

At the beginning, the WACR extracts the required features from the signals. As mentioned earlier, our reference feature is the cyclic profile of the SCF defined in (5). As an example, Figs. 2 and 3 show the cyclic profiles of the Sig1 and Sig4, respectively. Due to the symmetry of the cyclic profile around $\alpha = 0$, we take only half of the cyclic profile as our input feature vector. The extracted features are then applied to the classifier. For classifier training, 200 signals from each type of the four signals are used. Thus, the training input is an array

Table I
CONFIGURATIONS OF DIFFERENT CLASSIFIERS.

Classifier	Layers	Learning rate	Training cycles
ANN1	1 hidden layer with 2 neurons, and 1 output layer with 1 neuron	0.3	1000
ANN2	1 hidden layer with 4 neurons, and 1 output layer with 1 neuron	0.3	1000
ANN3	2 hidden layers with 4 neurons each, and 1 output layer with 1 neuron	0.3	1000
CNN1	1 convolutional layer with 5 filters of size 1×128, 1 average pooling layer with filter size 1×32, 1 rectified linear unit (ReLU), and 1 fully connected layer	0.1	900
CNN2	1 convolutional layer with 10 filters of size 1×256, 1 average pooling layer with filter size 1×64, 1 rectified linear unit (ReLU), and 1 fully connected layer	0.02	900

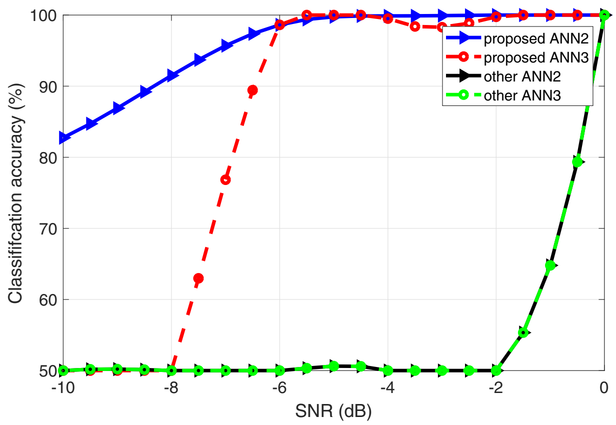

Figure 4. Test case 2: comparison between classification accuracy of the proposed technique based on cyclic profile feature "proposed" and another case with different type of features "other".

with 800 entries, where each entry represents a row vector of cyclic profile values corresponding to a signal. Another 800 signals are generated for the purpose of classifier testing.

In test case 1, Sig1, Sig2, Sig3 and Sig4 are used for both training and testing. Table II summarizes the classification accuracy in test case 1 with different classifiers and for different SNR values. From Table I, ANN1 consists of 1 hidden layer with 2 neurons and an output layer with 1 neuron. From Table II, the ANN1 performs well until SNR of -6 dB with a very high classification accuracy. At SNR= -8 dB, the performance of ANN1 degrades to the worst case in which radar signals are always falsely classified as communications signals. ANN2 has 1 hidden layer with 4 neurons. From Table II, at high SNR values, the classification accuracy of ANN2 is at the highest possible level. The performance of ANN2 starts to degrade when SNR value goes below -6 dB. At SNR= -10 dB, the classification accuracy becomes around 82% level.

We tested the effect of adding one more hidden layer on the performance with ANN3. However, compared with ANN2, using ANN3 didn't improve the performance as shown in Table II. As a result, comparing the different used ANNs, the ANN2 with 1 hidden layer and 4 neurons achieves the best performance. Another interesting scenario is to investigate the performance of proposed classification techniques with deep learning algorithms as in CNN1 and CNN2 cases. It can be shown from Table II that CNN1 performs well until SNR of -4 dB, after that the classification accuracy degrades to 50%. On the other hand, CNN2 with additional and large filters at the convolutional layer, can achieves better performance than CNN1 with classification accuracy close to the ANN2 as shown in Table II especially for low SNR values.

In test case 2, we made a comparison between the proposed classification scheme based on cyclic profile, named "proposed", and another classification scheme with different features, named "other" using the same signals that have been used in test case 1. In the "other" case we selected two features that were previously used in [4], [5]: bandwidth and standard deviation of the instantaneous frequency. From Fig. 4, the cyclic profile outperforms the other features case using different classifiers with SNR below 0 dB.

In test case 3, the radar signals that have been used for training the classifier are different from the ones that have been used for testing. Sig1, Sig2, Sig3 and Sig5 are used for training the classifier. On the other hand, the signals that are used for testing include Sig1, Sig2, Sig4 and Sig6. Table III summarizes the classification accuracy in test case 3 with different classifiers. As in test case 1, ANN2 and CNN2 achieve the best performance.

In test case 4, we evaluate the performance if the SNR value in training signals is different than the value in testing signals. Table IV shows the classification accuracy values in test case 4 with different SNR values. We kept the SNR value of the training signal at 0 dB level, while varying the SNR value of testing signals from 0 dB to -8 dB. For testing signals with SNR value of -4 dB, most of the classifiers achieve classification accuracy between 88% and 91.25%, except CNN1 that achieves 78.75%. By reducing the SNR level of testing signals below -4 dB, the performance of most of the classifiers degrades sharply with a noticeable superiority when using the ANN2.

These results show clearly that cyclic profile is a good candidate for classification between radar and communications signals even at low SNR values. This is because the cyclic frequencies can correspond to important signal features such as duty cycle, coding rate and modulation scheme that can discriminate between radar and communications signals. The cyclic profile enables us to use classifiers with simple configurations based on ANN and CNN. The best classification accuracy was achieved using ANN2 and CNN2. However, from the implementation and complexity perspectives, the ANN2 is more attractive choice than CNN2. This is because

Table II
TEST CASE 1: CLASSIFICATION ACCURACY WHEN TRAINING AND TESTING SIGNALS ARE THE SAME.

Classifier	SNR= 0 dB	SNR= -2 dB	SNR= -4 dB	SNR= -6 dB	SNR= -8 dB	SNR= -10 dB
ANN1	Training: 100% Testing: 100%	Training: 100% Testing: 100%	Training: 100% Testing: 99.88%	Training: 99.88% Testing: 98.12%	Training: 50% Testing: 50%	Training: 50% Testing: 50%
ANN2	Training: 100% Testing: 100%	Training: 100% Testing: 100%	Training: 100% Testing: 99.88%	Training: 100% Testing: 98.62%	Training: 99.25% Testing: 91.5%	Training: 99% Testing: 82.75%
ANN3	Training: 100% Testing: 100%	Training: 100% Testing: 99.75%	Training: 100% Testing: 99.5%	Training: 99.88% Testing: 98.62%	Training: 50% Testing: 50%	Training: 50% Testing: 50%
CNN1	Training: 100% Testing: 100%	Training: 100% Testing: 100%	Training: 99.88% Testing: 99.75%	Training: 50% Testing: 50%	Training: 50% Testing: 50%	Training: 50% Testing: 50%
CNN2	Training: 100% Testing: 100%	Training: 100% Testing: 100%	Training: 100% Testing: 99.88%	Training: 99.25% Testing: 98.62%	Training: 94.66% Testing: 91.13%	Training: 89.8% Testing: 80.5%

Table III
TEST CASE 3: CLASSIFICATION ACCURACY WHEN TRAINING AND TESTING SIGNALS ARE DIFFERENT.

Classifier	SNR= 0 dB	SNR= -2 dB	SNR= -4 dB	SNR= -6 dB	SNR= -8 dB	SNR= -10 dB
ANN1	Training: 100% Testing: 100%	Training: 100% Testing: 100%	Training: 100% Testing: 99.75%	Training: 99.88% Testing: 97.78%	Training: 50% Testing: 50%	Training: 50% Testing: 50%
ANN2	Training: 100% Testing: 100%	Training: 100% Testing: 99.88%	Training: 100% Testing: 99.62%	Training: 99.88% Testing: 97.75%	Training: 98.76% Testing: 91.63%	Training: 96.02% Testing: 83.87%
ANN3	Training: 100% Testing: 100%	Training: 100% Testing: 99.75%	Training: 100% Testing: 99.38%	Training: 50% Testing: 50%	Training: 50% Testing: 50%	Training: 50% Testing: 50%
CNN1	Training: 100% Testing: 100%	Training: 99.88% Testing: 99.88%	Training: 50% Testing: 50%	Training: 50% Testing: 50%	Training: 50% Testing: 50%	Training: 50% Testing: 50%
CNN2	Training: 100% Testing: 100%	Training: 100% Testing: 99.75%	Training: 100% Testing: 99.25%	Training:98.88% Testing: 98.62%	Training: 94.78% Testing: 92.25%	Training: 87.31% Testing: 82%

Table IV
TEST CASE 4: CLASSIFICATION ACCURACY WITH DIFFERENT SNR VALUES FOR TRAINING AND TESTING SIGNALS.

Classifier	Training SNR= 0 dB Testing SNR= -2 dB	Training SNR= 0 dB Testing SNR= -4 dB	Training SNR= 0 dB Testing SNR= -6 dB	Training SNR= 0 dB Testing SNR= -8 dB
ANN1	Training: 100% Testing: 99.62%	Training: 100% Testing: 90.12%	Training: 100% Testing: 73.5%	Training: 100% Testing: 53.88%
ANN2	Training: 100% Testing: 99.38%	Training: 100% Testing: 91.25%	Training: 100% Testing: 73.88%	Training: 100% Testing: 60.25%
ANN3	Training: 100% Testing: 98.88%	Training: 100% Testing: 88.5%	Training: 100% Testing: 70.5%	Training: 100% Testing: 58.25%
CNN1	Training: 100% Testing: 100%	Training: 100% Testing: 78.75%	Training: 100% Testing: 51.25%	Training: 100% Testing: 52.5%
CNN2	Training: 100% Testing: 99.75%	Training: 100% Testing: 88%	Training: 100% Testing: 72.75%	Training: 100% Testing: 55.25%

the implementation of CNN2 requires multiple hidden layers and complicated operations such as convolution and average pooling, while the ANN2 only has 1 hidden layer with 4 neurons.

V. CONCLUSION

In this paper we proposed and investigated techniques for discrimination between radar and communications signals using wideband autonomous cognitive radios. Two communications signals were selected: WiFi and LTE, and experimented versus wide range of different radar signals. The radar signals included linear frequency modulation (LFM) pulse, biphase-coded pulse, Barker-coded pulse and Frank-coded pulse. The cyclic profile was used as the reference feature to distinguish between the signal types. Two different classification tools were investigated in this work for comparison purpose: artificial neural networks (ANNs) and convolutional neural network (CNNs). Several test cases evaluated the performance of the proposed classification techniques from different perspectives. Simulation results showed that it is indeed possible to discriminate between the radar and the communications signals, even at very low SNRs, if the right configurations for the proposed classifiers were chosen. Furthermore, the efficiency of cyclic profile was shown compared to other types of features, such as, bandwidth and standard deviation of the instantaneous frequency.

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