Automatic Radar Waveform Recognition using the Wigner-Ville distribution and AlexNet-SVM

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***Abstract*—In this paper, we propose a radar signal modulation algorithm to recognize three different radar signals amidst other wireless communication waveforms, including Barker, linear frequency modulation, and rectangular codes. First we extract the features of the original signal by computing its smoothed pseudo Wigner-Ville distribution. Second, we construct a transfer learning-based convolutional neural network over AlexNet to further extract features from the time-frequency images. Finally, a support vector machine classifier is applied for the signal classification. We also perform a similar analysis with models which use AlexNet for both feature extraction, and classification tasks. Results show that the proposed model which incorporates the linear classifier, achieves the highest recognition accuracy of 97.8%.**

***Index Terms*—Feature extraction, neural network classifier, time-frequency analysis, radar waveform recognition, deep learning.**

I. Introduction

With the mounting number of different communication and radar emitters and waveforms, combined with the increasing datarate demands in communication systems, the need for efficient and agile use of the electromagnetic spectrum has arisen. Automatic radar waveform recognition is thus a fundamental process in electronic warfare (EW) applications, such as radar emitter recognition, cognitive radar, and threat detection [1]. Numerous methods have been proposed for the recognition of radar signals of different modulation types. These methods consist of two steps: feature extraction and classifier design. Although it is important to have an efficient classifier, the key task that needs to be perfected is feature extraction. Lunden *et al.* [1], for example, derive features based on time-frequency analysis (TFA), Wang *et al.* [2] derive features based on auto-correlation functions (ACF), while Pu *et al.* [3], characterize the frequency change of radar signals based on instantaneous frequency analysis (IFA). Machine learning techniques have previously been employed for the classifier design and applied directly to the extracted features [4], [5]. Such techniques include support vector machines [6], artificial neural networks [7], and convolutional neural networks (CNN) [8]. The above discussed conventional two-step recognition method have one main deficit. There is a need to obtain discriminative features, and most of the time the extracted features are not discriminative enough for recognition. For instance, IFA is quite sensitive to noise, while ACF is more robust and hence performs better than the IFA based method. With deep learning-based methods, the need for feature extraction has been greatly downplayed, as most of these networks are capable of learning their own features and have been proven to be more accurate than the classical methods [8]. Although it is not necessary to perform feature extraction, the representation of the radar signal which is used as the input could yield different results. One peculiar characteristic of radar waveforms is their frequency variation with time. TFA transforms one-dimensional signals into time-frequency images (TFI), which clearly shows the pattern of frequency variation. Previous works have applied CNN to TFI images for automatic radar waveform recognition purposes [8]. In this work however, we introduce a neural network architecture composed of the AlexNet CNN model and a SVM classifier, and apply this proposed architecture for the recognition of TFIs of radar signals amidst other wireless communication waveforms.

The remainder of the paper is structured as follows. Section II describes the time frequency representation. Section III introduces the proposed model architecture. Section IV gives the simulation process and discuses the results obtained. Finally, section V concludes the paper.

II. Time-Frequency representation and Image Processing

The Wigner-Ville distribution (WVD) is a common method used to perform TFA. It computes the Fourier transform of the ambiguity function (AF) of the signal as follows:

$$AF(\tau) = x(t-u+\tau/2)x^*(t-u-\tau/2), \tag{1}$$

where $x(t)$ is the discrete time-signal sampled from time $t = 1, \ldots, T$, and τ and u are discrete variables. The AF represents the generalization of the auto-correlation function of the signal. In the case where there are signals with several frequency components, the WVD suffers from the so called cross-terms. In this paper, we adopt the smoothed pseudo Wigner-Ville distribution (SPWVD), which reduces the effects of cross-terms and improves the time-frequency distribution. The SPWVD is a three-dimensional representation of an input signal (time, frequency, amplitude), ideally suited for defining

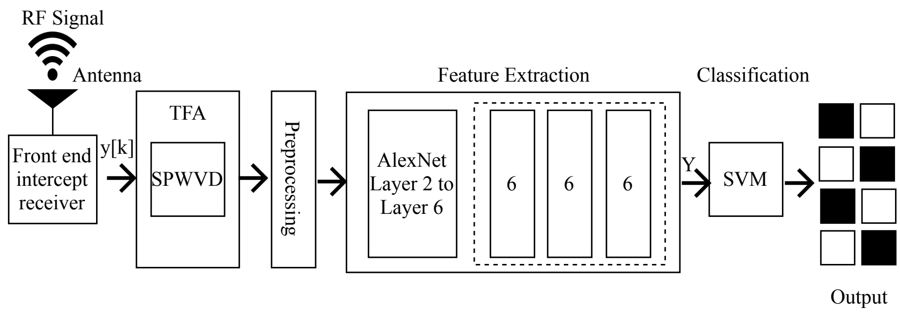

Fig. 1. Proposed AlexNet-SVM radar waveform recognition System.

transient or non-stationary phenomena [9]. In this paper, we define the SPWVD as

$$p(t,f) = SPWVD_x(t,v) = \int_{\infty}^{\infty}\int_{\infty}^{\infty} g(u)h(\tau) \\ x(t-u+\tau/2)x^*(t-u-\tau/2)e^{-\jmath 2\pi v\tau}\partial u\partial\tau, \quad (2)$$

where, v is the frequency shift, τ is the time lag, $g(u)$ and $h(\tau)$ represent real window function, and $g(0) = h(0) = 1$ After the SPWVD function is applied to each of the signals, the result is composed of TFIs. These TFIs are down-sampled to 227×227 matrices. This is due to the fact that the pretrained network which we would use was trained on images of input size $227 \times 227 \times 3$.

III. Proposed System Model

In this section we summarize our radar waveform recognition system as represented in Fig.1. The intercepted radio frequency (RF) signal gets amplified by a low noise amplifier (LNA), down-converted to the intermediate frequency (IF) f_l and then sampled at $f_s(= 1/T_s)$ to produce discrete time signal $y[k]$ as

$$y[k] = x[k] + w[k] = \alpha[k]e^{\alpha\theta[k]} + w[k], \quad (3)$$

where $x[k]$ is the down-converted (to f_l) discrete time complex radar signal samples, $w[k]$ is the complex additive white Gaussian noise (AWGN) process with two side power spectral density $N_0/2$, $a[k]$ is the non-zero constant signal envelope (i.e., amplitude), $\alpha = \sqrt{-1}$ is the imaginary unit, k is the sample index increasing every T_s for a sampling frequency f_s, and $\theta[k]$ is the instantaneous phase of the intercepted signal. The instantaneous phase can be deined as:

$$\theta[k] = 2\pi f[k](kT_s) + \phi[k] \quad (4)$$

This discrete time signal $y[k]$ gets fed into the TFA block, where the SPWVD is applied. The generated TFIs are then forwarded to the processing block, where they are resized to produce the input (i.e., training and test data) to the AlexNet-SVM network.

A. Convolutional Neural Network

Feature extraction is a very important aspect of the radar recognition system. In this paper, we aim to extract the essential features of the TFIs, and thus utilize the feature extractor: AlexNet based on transfer learning.

The structure of AlexNet is composed of a sequence of functions in the order: {Input, Conv1, ReLu1, Pooling1, Norm1, Conv2, ReLu2, Pooling2, Norm2, Conv3, ReLu3, Conv4, ReLu4, Conv5, ReLu5, Pooling6, FC6, ReLu6, Drop6, FC7, ReLu7, Drop7, FC8}. In this structure, every instance of Conv represents a convolution layer, ReLu indicates the rectified linear unit activation function, Pooling is the max-pooling layer, Drop is the dropout layer, and FC is the fully-connected layer. There are two stages in the training process of the network, the forward and back propagation. Firstly, a number of training samples are extracted in a certain ratio and inputted into the initialized network. A convolutional kernel was used to obtain the features of the convolutional layer. This network constructs a hierarchical representation of input images. The deeper layers contain higher-level features, which were constructed by the lower-level features of earlier layers. In order to get representations for the training and test images, we use activations on the fully-connected layer FC7. Fundamentally, we keep the parameters of AlexNet unchanged, and truncate the model. In particular, we take the input layer to the fully-connected layer of ALexNet as the FC7 feature transfer extraction module.

B. Support Vector Machine

The SVM is a linear classifier, which uses a technique based on the structural risk maximization principle and have the ability to generalize to new data [6]. The SVM transforms the input vector into the high-dimensional feature space through nonlinear mapping, constructs the optimal classification hyper-plane in the high-dimensional feature space, and classifies the samples of high-dimensional space. The SVM algorithm is summarized in Algorithm 1, where Y represents the extracted features, which are then split to obtain Y'. d indicates the dimension of the feature space, while $\phi(d)$ indicates a higher dimension of the feature space.

IV. Simulation and Discussion

In this section, we used MATLAB to generate the following radar signals: rectangular (Rect), linear frequency modulation (LFM), Barker code, Gaussian frequency shift-keying (GFSK), continuous phase frequency shift-keying (CPFSK), broadcast

Algorithm 1 Support Vector Machine Recognition Algorithm

Input: Features, Y

Output: Categories

1: Split data: $[Test\_Y, Train\_Y] \leftarrow Y^{'}$

2: Map to a high dimensional space:

$$\phi(d) = (\phi(d_1), \ldots, \phi(d_n)) \leftarrow d(d_1, \ldots, d_n) \leftarrow Y^{'}$$

3: Find the optimal hyper plane - parameter optimization

4: **return** Categories

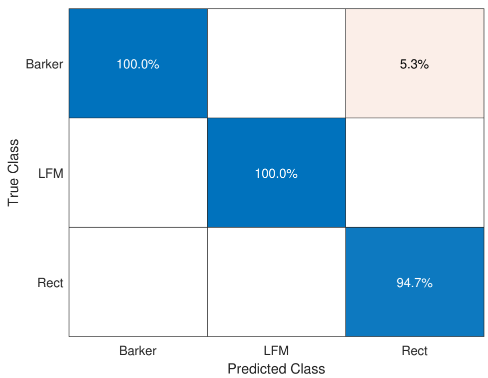

Fig. 2. Confusion Matrix for the recognition results obtained by using AlexNet for feature extraction and classification on the three radar signals. The overall RSR is 98%.

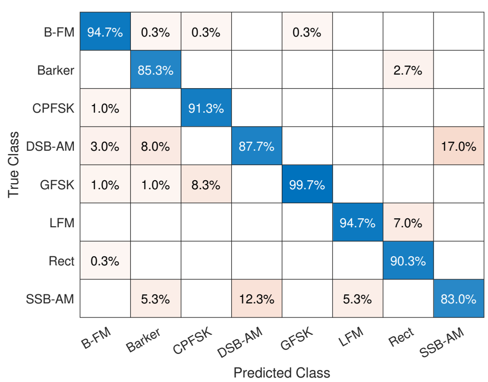

Fig. 3. Confusion Matrix for the recognition results obtained by using AlexNet for feature extraction and classification. The overall RSR is 86.4%.

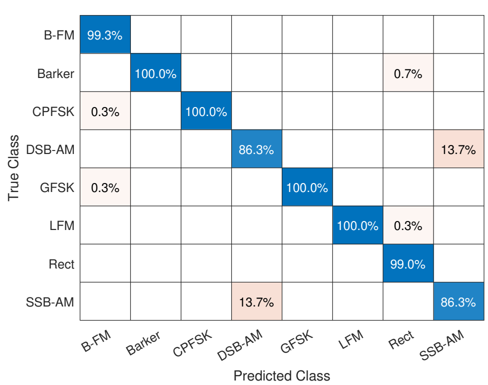

Fig. 4. Confusion Matrix for the recognition results obtained by using AlextNet for feature extraction and SVM for classification. The overall RSR is 97.8%

frequency-modulation (B-FM), double side-band amplitude moulation (DSB-AM), and single side-band amplitude modulation (SSB-AM). All signals were generated with a sample-rate of 100 MHZ for each modulation type. Each of the signal have unique parameters and incorporates different impairments which makes it more realistic. We randomly generated the pulse width and repetition frequency for each waveform. The sweep bandwidth and direction for the LFM waveforms were randomly generated. The chip width and number for Barker waveforms were also randomly generated. All the signals were impaired with white Gaussian noise with a random signal-to-noise ratio which is in the range of $[-6, 30]$ dB. A frequency-offset with a random carrier frequency in the range of $[f_s/6, f_s/5]$ is applied to each signal, and then passed through a multi-path Rician fading channel. For every type of signal modulation, 1000 data groups were generated, from which 80% were used for training and 20% for testing.

We initially generated 3000 radar signal simulation samples for three modulation types, and then trained an AlexNet model to recognize these signals.these signals were first converted to TFIs through a TFA. The TFIs are down-sampled to the same input size of the AlexNet model. In this case, the AlexNet model performs the task of feature extraction and classification. The result is summarized in Fig. 2, where a near-perfect distinction of the three signals and a recognition success rate (RSR) of 98% can be seen.

In real-world scenarios however, the frequency spectrum of a radar classification system must compete with other transmitted sources, therefore, we incorporated other simulated modulation types, and like before, we trained an AlexNet model to recognize these signals. Fig. 3 shows the confusion matrix, where it can be observed that the RSR of the radar signals is reduced due to the presence of other communication signals.

In order to test our proposed model, We obtained the features of these signals and their labels with the pretrained neural network, which has learned rich feature representations for a wide range of images. The extracted features from the training images are then used to fit a multi-class SVM, while the test images are classified using the trained SVM model and the features extracted from the test images. Fig. 4 shows that the RSR improved to 97.8%. It can be inferred that the introduction of an SVM into the model improves the performance of the recognition system. In addition, the transfer learning-based AlexNet that we used to extract the features, does not start training from scratch, optimizing training time and resources.

V. CONCLUSION

This paper proposes a radar signal modulation-recognition model, which uses feature extraction methods based on Wigner-Ville distribution, a pre-trained convolutional neural network AlexNet, and a support vector machine-based classification model. The performance of the modulation-recognition model was verified using generated samples for three radar signals and five communication waveforms. The proposed model reaches a recognition accuracy of 97.8%, proving a remarkable robustness over all the range of randomly generated SNRs. In the future, we plan to use the model to recognize signals at specified SNRs for extended application value.

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