IJE TRANSACTIONS B: Applications Vol. 36, No. 08, (August 2023) 1459-1467

International Journal of Engineering

Journal Homepage: www.ije.ir

A Noise-aware Deep Learning Model for Automatic Modulation Recognition in Radar Signals

M. Aslinezhad[a], A. Sezavar*[b], A. Malekijavan[a]

[a] Department of Electrical Engineering, Shahid Sattari Aeronautical University of Science and Technology, Tehran, Iran
[b] Department of Electrical and Computer Engineering, University of Birjand, Birjand, Iran

PAPER INFO

Paper history:
Received 24 March 2023
Received in revised form 08 May 2023
Accepted 13 May 2023

Keywords:
Modulation Classification
Deep Learning
Noise-aware Systems

ABSTRACT

Automatic waveform recognition has become an important task in radar systems and spread spectrum communications. Identifying the modulation of received signals helps to recognize different invader transmitters. In this paper, a noise aware model is proposed to recognize the modulation type based on time-frequency characteristics. To this end, Choi-Williams representation is used to obtain spatial 2D pattern of received signal. After that, a deep model is constructed to make signal clear from noise and extract robust and discriminative features from time-frequency pattern, based on auto-encoder and Convolutional Neural Networks (CNN). In order to reduce the effect of noise and adversarial disorders, a new database of different modulation patterns with different AWGN noises and fading Rayleigh channel is created which helps model to avoid the effects of noise on modulation recognition. Our database contains radar modulations such as Barker, LFM, Costas and Frank code which are known as frequently used modulations on wireless communication. Infact, the main novelty of this work is designing this database and proposing noise-aware model. Experimental results demonstrate that the proposed model achieves superior performance for automatic classification recognition with 99.24% of accuracy in noisy medium with minimum SNR of -5dB while the accuracy is 97.90% in SNR of -5dB and f=15 Hz of Doppler frequency. Our model outperforms 5.54% in negative and 0.4% in positive SNRs (even though with less SNR).

***doi**: 10.5829/ije.2023.36.08b.06*

1. INTRODUCTION

Nowadays, digital communication plays a critical role in human life. By growing the number of transmitters in industrial mediums, i.e., Internet of Things (IoT), and with the limitation in telecommunication channels, using Cognitive Radio (CR) communications has been grown up. One of the necessary tasks for receivers is to identify the parameters of receiving unknown signals, such as kind of modulation. Therefore, Automatic Modulation Classification (AMC) can play a significant role in cognitive radio and Electronic Intelligence (ElInt). AMC is important for communication monitoring, spectrum awareness and adaptive communication [1] . AMC is necessary for both civilian and military services. One of the important applications of AMC can be sensed in Electronic Warfare (EW) in which receiver should be able to detect the modulation of unknown and adversarial signals. Beside cognitive radio, AMC is critical for radar radar receivers since waveform of modern signals can be changed in every pulses [2].

Researches in AMC have denoted two main categories, using Likelihood for blind classification and using feature extraction for detecting the kind of modulation. Since likelihood-based methods are time consuming with high computational complexity, feature based methods are more popular. In this way, blind modulation detection is done by extracting features from received signals and based on them, determine which modulation is used. Although there are different methods for feature extraction such as extracting hand-crafted features and extracting features based on machine learning, there still are some important challenges for AMC such as noisy mediums, adversarial attacks, multipath fading, and time varying and frequency

*Corresponding Author Email: a.sezavar@birjand.ac.ir (A. Sezavar)

Please cite this article as: M. Aslinezhad, A. Sezavar, A. Malekijavan, A Noise-aware Deep Learning Model for Automatic Modulation Recognition in Radar Signals, ***International Journal of Engineering, Transactions B: Applications***, Vol. 36, No. 08, (2023), 1459-1467

selective channels which lead us to implement more robust and reliable systems.

In this paper, a noise-aware model is defined based on Choi-Williams transform and hybrid deep learning networks. To this end, received signal is converted to 2-D image which illustrates frequency features versus time and hybrid deep models learn to remove noises and extract robust features and classify the type of modulation. Also, a database of some important modulation with different amounts of noise is created to help models overcoming on noise effect. Block diagram of AMC by converting signal to images is illustrated in Figure 1. The novelty of the proposed method is designing arbitrary database in order for train and evaluate AMC systems. Also, a new combined noise-aware medoel is designed by combining auto-encoders and CNN which is able to overcome noise challenges. The rest of this paper is constructed as follows. Literature review of recent works on AMC is on section 2. In section 3, a brief introduction of Choi-Williams method and Convolutional Neural Networks (CNNs) are denoted following by detailed of the proposed method. Experimental results and implementation setups are shown in section 4 in which, and section 5 concludes the paper.

2. RELATED WORKS

As mentioned before, because of complexity of likelihood-based methods, feature-based models are more popular. Classical approached of feature extraction have used hand-crafted methods. Aslam et al. [2] used a combination of KNN and genetic algorithms for modulation detection of four different types of digital modulations. They have used comulants hand-crafted features in order to classify by KNN. Abdelmutalab et al. [3] used high order comulants features of received signal in order to determine the modulation by defining hierarchical polynomial classifier. Their system has achieved accurate results on two types of modulations, M-PSK and M-QAM. Saharia et al. [4] used different strong features from time, frequency and statistics domain of received signals to determine the kind of modulation. After extracting features, a Random Forest (RF) classifier was trained to identifying the modulation.

Most of recent researches on AMC have used machine learning methods especially deep learning. Several researches have used deep CNNs for extracting features from radio signals and classified them [5-9]. Since we want to use 2D inputs as images for CNNs, some resent works which converts received signals into 2D inputs are presented. Yar et al [10] used Short Time Fourier Transform (STFT) to convert raw signals to images. Before using CNN to classify input images, Hough transform was used to illustrate pulses as a single line in each image. Choi-Williams transform has been used in [11] to obtain 2D time-frequency images of modulated signals. After that, Zhang et al. [11] used CNN to classify time-frequency images and determine the kind of modulation. Although reviewed works and some other researches have achieved good results, they are limited on few number of modulations and in normal noisy channels [12]. Therefore, we need model to work in different arbitrary noise and attacks more reliable.

3. METHODOLOGY

Since we are using Choi-Williams 2D transform to obtain time-frequency images, it is needed to briefly review it and find find more about it. Also, CNNs as a powerful tool of deep learning models should be introduced. So, before going on to the proposed method, 2D transform and CNN are briefly introduced.

3. 1. Time-frequency Distribution In order to obtain 2D images from raw signal, plotting time-frequency distribution can be useful. Although there exist some transforms which produce time-frequency analysis, Choi-Williams transform is preferred because of its advantages in removing cross-term interference. Giving raw signal as $u(t)$, Choi-Williams distribution can be obtained as follows [11, 13]:

$$CW(f,t) = \iiint_{-\infty}^{+\infty} u(s+{}^{\tau}/_{2}).u^{*}(s-{}^{\tau}/_{2})k(\lambda,\tau)e^{j2\pi\lambda(s-t)}e^{-j2\pi f}d\lambda ds d\tau \tag{1}$$

$$k(\lambda,\tau) = \exp\left({}^{(\pi\lambda\tau)^2}/_{2\sigma}\right) \tag{2}$$

In which, $CW(f,t)$ denotes the time-frequency distribution and $k(\lambda,\tau)$ is a low-pass filter which helps to refuse cross-term interference and σ controls the bandwidth of the filter. By plotting $CW(f,t)$, image can be obtained and can be processed.

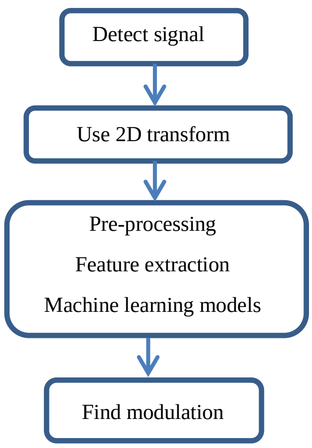

Figure 1. Block diagram of AMC using 2D transforms

3. 2. Deep Learning Deep learning is a new machine learning approach in which high-level features are extracted from input data using hierarchical layers [14]. Deep learning has demonstrated excellent data processing performance by achieving excellent accuracy in image [15-18], video[19], natural language processing [20], time series [21] and audio processing [22]. Convolutional Neural Networks (CNNs) are among the deep learning algorithms that are suitable for image processing [23, 24]. Guo et al. [14] have specifically designed CNNs for two-dimensional (2D) data such as image and video, and they also have superior image processing accuracy.

Deep learning differs from previous processing methods in that data is fed directly to the system in order to extract features, whereas in traditional processing, hand-crafted features were fed to algorithms for processing or classifying, such as artificial neural networks and other classifiers. In CNN, data is fed to the network which consists of some convolutional, pooling and fully-connected layers. During the training process, weights of convolutional kernels learn to extract meaningful features and fully-connected layers learn to classify these features to related category. Thus, the input image goes throw these hierarchical layers to extract feature and determine in which class the input belongs.

3. 3. Auto-encoder An auto-encoder is a multilayer neural network that employs encoder and decoder layers to reconstruct input [25]. In the encoder, an input image (or signal) is sent to a network where features are extracted and a tiny vector is created by downsampling. The decoder then uses supervised learning to attempt to rebuild the input by feeding it the encoded feature vector. Auto-encoders have been utilized for a variety of applications, including feature extraction and denoising in image processing [26-28].

3. 4. Implemented Method As any supervised learning model, the implemented method consists of train and test phase. To create the database, four different kinds of modulation, Barker, LFM, Costas and Frank code, are randomly created. Then, arbitrary AWGN noises with different SNRs are added to them in order to create input signal, $x(t)$ by:

$$x(t) = r(t)m_i(t) + n(t,s) \tag{3}$$

where $\mathrm{m_i(t)}$ denotes the modulated signal and $i \in$ (Barker, LFM, Costas and Frank code), $r(t)$ indicates Rayleigh fading channel described in Equation (4) and $n(t,s)$ refers to AWGN noise and s is parameters to control SNR.

$$r(t) = Ke^{j(2\pi f+\theta)} \tag{4}$$

where K is the gain of Rayleigh fading channel, f denotes Doppler frequency shift and θ is phase of path.

In order to make system noise aware and be able to overcome noises and fading effects, Artificial Distributed Signals (ADS) are created. These signals are used then to train auto-encoder to create clear transforms of signals. By adding random noises in different amounts of Doppler frequency shifts, the ADS is created in the form of Equation (3). By using Equation (1), 2D transform of each input signal is created and stored as a RGB color image. If we show the decoder and encoder performances by $\mathrm{D(.)}$ and $\mathrm{E(.)}$ respectively, the loss function for training auto-encoder is defined as follows:

$$L = \sum_i \sum_j \sqrt{(D(E(cw'(i,j)) - cw(i,j))^2} \tag{5}$$

In which, $cw'(i,j)$ is the 2D transformed of ADS and $cw(i,j)$ is the 2D transform of $\mathrm{m_i(t)}$. the training concept of auto-encoder is illustrated in Figure 2.

In training step, the train batch images are fed to CNN and during the training, until the loss function is minimum, kernel weights are updated in order to extract best features. Output of each convolution layer is calculated as follows:

$$C = Max(0\ , \sum_{i=1}^{K} \sum_{j=1}^{K} p(i,j) \times h(i,j)) \tag{6}$$

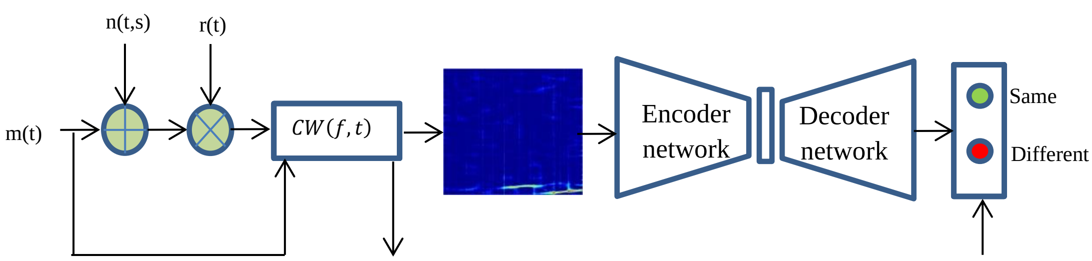

Figure 2. Training concept of auto-encoder for reconstructing main signal from ADS

In which, p is the value of pixel and h denotes the weight of filter and in order to model nonlinearity, maximum of convolution and 0 is calculated (ReLU function) and kernel size of each filter is $K \times K$. In the pooling layer, among $N \times N$ pixels, the maximum value is selected and rests of them are ignored. After some convolution and pooling, the model is followed by some fully-connected layers in which, neurons calculate a linear combination of all data in feature vector and activation function also is used to model nonlinearity. Output of each neuron is as follows:

$$f = Max\left(0\ ,\sum_{j=1}^{K} w_i \times n_i\right) \quad (7)$$

where n_i denotes a feature of is previous layer and w_i is the relevant weight to it. After training, the model is learned to extract robust features and classify them in order to distinguish type of the modulation of input signal. The structure of the implemented method is illustrated in Figure 3 and the algorithm of the proposed method is demonstrated in Algorithm 1.

Algorithm 1: proposed noise-aware deep model for modulation classification

Train
for i in {Barker, Frank, Costas and LFM} **do**:
Create random $m_i(t)$
Compute CW using Eq.2 and Eq.3
Initialize K, f , θ and s
$r(t) = Ke^{j(2\pi f+\theta)}$
$x(t) \leftarrow r(t)m_i(t) + n(t,s)$
Compute CW' using Eq.2 and Eq.3
Train auto-encoder
Initialize w_i for layers and L
While $L < \mathcal{E}$:
$L^{t+1} \leftarrow \sum_i \sum_j \sqrt{(D^t(E^t(cw'(i,j)) - cw(i,j))^2}$
$D^{t+1} \leftarrow D^t$
$E^{t+1} \leftarrow E^t$
Train CNN
Initialize w_i
While max_itteration is not reached:
For all filters and neurons in all layers **do**:
$C^t = Max\left(0\ ,\sum_{i=1}^{K}\sum_{j=1}^{K} p^t(i,j) \times h^t(i,j)\right)$
$f^t = Max\left(0\ ,\sum_{j=1}^{K} w_i{}^t \times n_i{}^t\right)$
$t \leftarrow t+1$
End
End
Test
Compute CW of input signal using Eq.2 and Eq.3
Compute $(D(E(CW)))$
Feed to trained CNN
Find argmax(labels)

4. RESULTS

In this section, before going to details of implementation and results, the dataset which is created for this paper is illustrated in subsection 4.1.

4. 1. Dataset In order to prepare data for training CNN, four different kinds of modulation are considered, Barker, Costas, Frank code and LFM. For each kind of modulation, 120 random and different signals are created for training, with different amounts of AWGN noises with different SNR from -5dB to 5dB and 36 signals for test. Thus, we create totally 624 random noisy signals and transferred them to 624 RGB images. Some samples of created images for LFM modulation are shown in Figure 4.

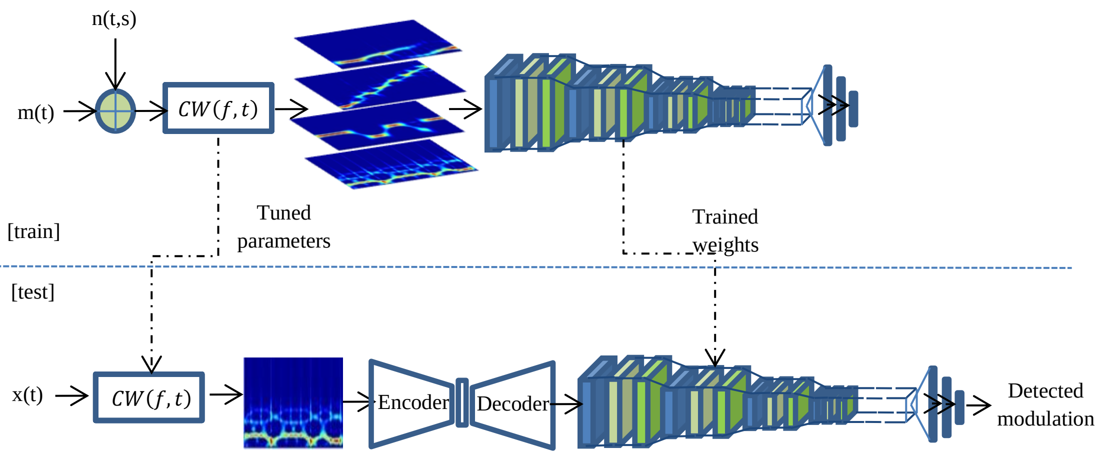

Figure 3. Diagram of the proposed method in train and test steps

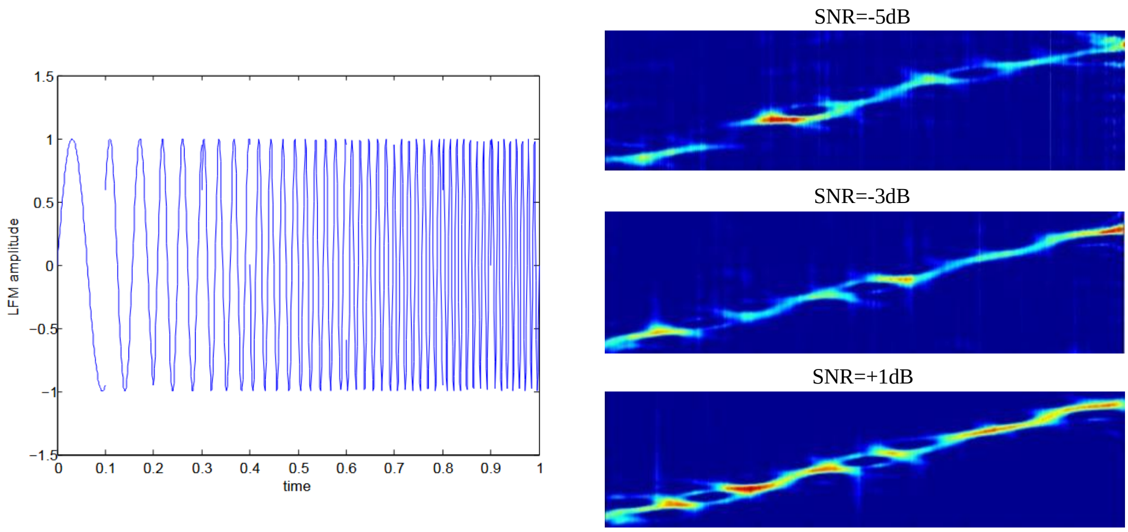

Figure 4. Samples of created images for a random LFM signal with different SNR

4. 2. Simulation Details To go to the details of implementation, it is noticed that codes are written using python language using necessary libraries such as Tensorflow and Keras[1]. For computing 2D images, Matlab is also used. The simulation was done on 8 GB of RAM and core i-5 Intel CPU. For training auto-encoder and CNN, best hyper-parameters are obtained by tuning different amounts. The loss functions for auto-encoder and CNN was Binary and Categorical Cross-entropy, respectively; minimizing by Adam optimizer with Learning-rate of 0.005. For training, data is randomly divided to training (80%) and validation (20%) set. Because the model performs the same in training and validation data, it is understood that it can be used generally for new data with high performance. Also, by looking loss function curves of auto-encoder, it is found that the auto-encoder is trained well and is able to reconstruct input image clearly.

4. 3. Numerical Results In order to show the performance of auto-encoder, some input noisy signals and output examples of the trained auto-encoder is illustrated in Figure 5 in which, four different samples of created ADS are shown. The first one is Barker signal with SNR=-4db in Rayleigh fading channel with Doppler frequency of 5 Hz. After using the auto-encoder, the pattern is clearly reconstructed and most parts of noises are removed as well as in other samples. It can be seen from this figure than Costas signal even with -5dB of SNR and 10 Hz of Doppler frequency is reconstructed well and clear. Results of implementing the proposed method with different SNR from 1 dB to -5 dB are illustrated under the Rayleigh fading channel with four different Doppler frequencies, 0, 5, 10 and 15 Hz. For each Doppler frequency, one diagram is considered which compares the accuracies of detection under different SNRs of white Gaussian noises.

From Figure 6, it can be found that in f=0HZ, accuracies for LFM code are upper than other and decreases from 100% to 98.6% in SNR -5dB. It can be understood that reducing 5 dB of SNR decreases just 1.4% of performance and it means that noise-aware part of model prevent noises to lack performance very much. Also, by increasing frequency to 15 Hz (which means the worthy of fading channel), accuracy of LFM falls to 98.41%. Therefore, it can be understood that the proposed model performs well even with an increase in the effect of fading Rayleigh channel. The lowest accuracy belongs to Costas modulation which is 97% in -5 dB and f=0 Hz and decreases to 96.94 in -5dB and f=15 Hz. As an ablation study, separate performance with different amount of noises and Doppler frequencies of fading channel for the proposed method, the proposed without auto-encoder and two other famous deep CNNs, are illustrated in Table 1. Based on Table 1, it can be found that although by using well-known CNNs such as VGGNet [29] and ResNet50 [24] and transfer learning, good performance can be achieved, but it will decease meaningful by decreasing SNR and increasing Doppler frequency in Rayleigh fading channel. Using the proposed method, the performance is more stable against different situations. In order to compare the results with the related works of AMC, accuracy of the proposed method and some related and new researches are shown in Table 2. To compare, the performance is computed in AWGN channel without fading.

As can be seen in Table 2, model proposed by Zhang et al. [11] achieved 93.7% of accuracy by combining CNN and image processing technique such as denoising and binarization on 8 different kinds of modulation.

[1] Https://keras.Io/

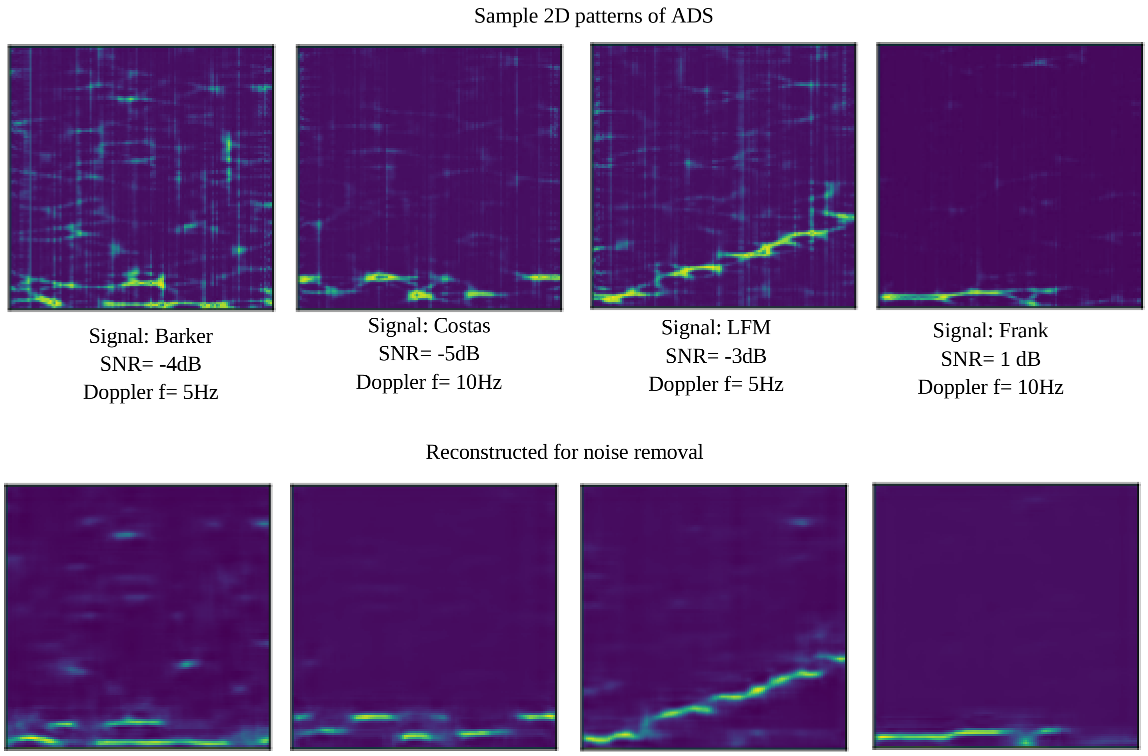

Figure 5. Samples of different ADS (first row) and their relative cleared pattern after the proposed auto-encoder (second row)

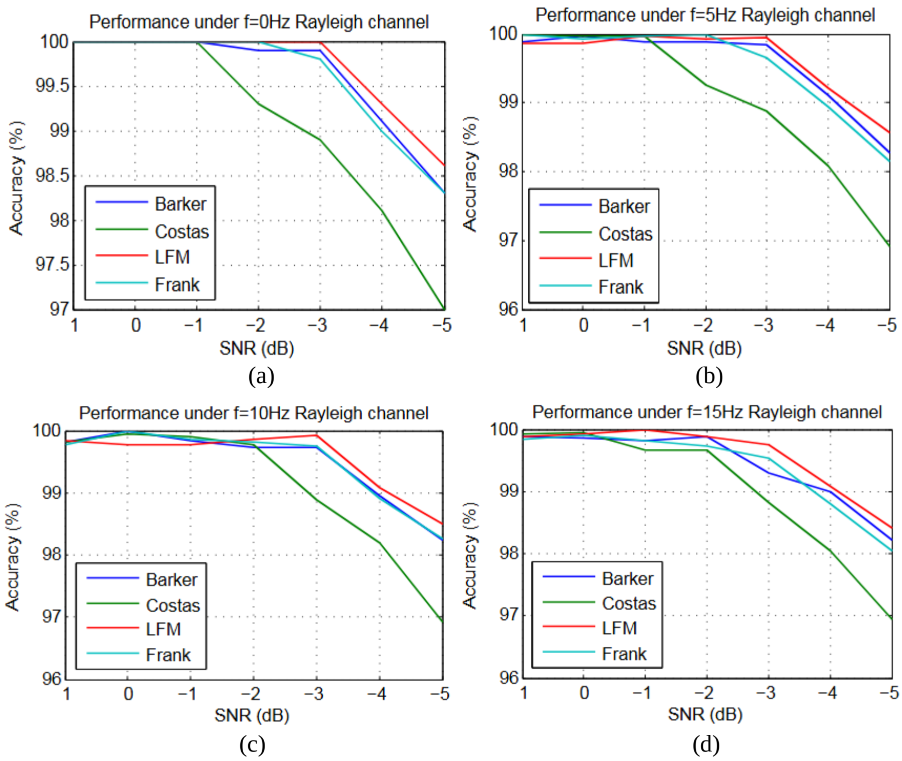

Figure 6. Comparison the accuracies of detection different modulations under different SNRs of white Gaussian noises with four Doppler frequencies, 0, 5, 10 and 15 Hz shown in part (a), (b), (c) and (d), respectively

TABLE 1. Numerical results and ablation for different methods under AWGN noises with SNR=0dB and -5 dB and Doppler frequencies of Rayleigh fading channel with f=5Hz, 10Hz and 15Hz

		Doppler f=5 Hz		Doppler f=10 Hz		Doppler f=15 Hz	
Model	**modulation**	**SNR=0dB**	**SNR=-5dB**	**SNR=0dB**	**SNR=-5dB**	**SNR=0dB**	**SNR=-5dB**
VGGNet	**Barker**	98.15%	90.91%	93.20%	89.80%	90.13%	81.70%
	Costas	96.73%	88.23%	91.99%	84.20%	86.07%	78.16%
	LFM	99.03%	97.03%	97.70%	88.37%	89.43%	82.84%
	Frank	98.08%	94.05%	93.86%	85.92%	88.03%	79.01%
ResNet50	**Barker**	99.01%	92.70%	94.56%	91.17%	92.47%	89.21%
	Costas	95.03%	90.42%	92.51%	88.49%	88.82%	81.40%
	LFM	98.99%	96.86%	97.51%	93.13%	92.24%	89.42%
	Frank	97.04%	92.17%	94.46%	89.18%	90.11%	84.51%
CNN (without transfer learning)	**Barker**	98.30%	91.48%	94.32%	90.06%	91.82%	87.63%
	Costas	96.23%	89.70%	91.09%	86.41%	87.19%	82.96%
	LFM	99.30%	97.72%	98.03%	94.93%	95.14%	93.02%
	Frank	98.21%	95.42%	96.06%	91.73%	93.51%	89.86%
CNN+AE (the proposed)	**Barker**	**100%**	**98.27%**	**100%**	**98.25%**	**99.86%**	**98.22%**
	Costas	**100%**	**96.91%**	**99.94%**	**96.92%**	**99.95%**	**96.94%**
	LFM	**100%**	**98.56%**	**99.97%**	**98.49%**	**99.93%**	**98.41%**
	Frank	**99.93%**	**98.16%**	**99.91%%**	**98.25%**	**99.90%**	**98.04%**

TABLE 2. Comparison between the proposed method and some state-of-the-art models for AMC in AWGN noises

Method	SNR	Description	Accuracy
CNNBD [11]	-2dB	CNN+binarization +denoising	93.7%
SCNN [10]	-10dB, 10dB	STFT+CNN	68.27%, 93.7%
SVMCNN [32]	2dB, +20dB	SVM+CNN	82.27%-98.52%
FCNN [33]	-10dB, +20dB	Fusuion CNN	0.09%-99.96%
3DCNN [5]	8dB, 25dB	3D CNN	98.1%, 99.6%
The proposed	-5dB, 0dB	CNN+nosie-aware training	99.24%, 100%

Combining CNN with different feature representation such as Short Term Fourier Transform (SIFT) and Support Vector Machine (SVM) leads to maximum accuracy of 93.73% and 98.52% in +10dB and +20 dB noises [10, 30]. However, between state-of-the-art models, fusion CNN [31] has achieved 99.96% of accuracy in +20dB noise and variation between accuracies are 98.1% and 99.6% in 3DCNN [5]. The proposed model achieves 100% accuracy when the SNR is 0 dB and 99.24% in the noisy environment with SNR= -5 dB which means that our method can be used generally and reliably in noisy medium.

5. CONCLUSION

Since Automatic waveform recognition is an important and challengeable task in radar systems and spread spectrum communications, this paper aims to implement a robust system for modulation classification in noisy medium. To this end, an arbitrary noisy database is created in which, different kinds of Barker, LFM, Costas and Frank code modulation in different AWGN noises are demonstrated under different Doppler frequencies of fading Rayleigh channel. Therefore, a system is implemented using Choi-Williams distribution to achieve and plot 2D features and by combining convolutional neural network and auto-encoder for training on the crated database. Experimental results showed that the proposed model outperforms new models by achieving 99.24% accuracy in minimum SNR of -5dB while the accuracy is 97.90% in SNR of -5dB and f=15 Hz of Doppler frequency. Numerical results proof that the model can be used generally on automatic modulation classification since the performance is stable in different noisy environments

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Persian Abstract

چکیده

امروزه تشخیص خودکار مدولاسیون به یک وظیفه مهم در سیستم های راداری و ارتباطات طیف گسترده تبدیل شده است. شناسایی مدولاسیون سیگنال های دریافتی به شناسایی فرستنده های مهاجم مختلف کمک می کند. در این مقاله، یک مدل آگاه از نویز برای تشخیص نوع مدولاسیون بر اساس ویژگی‌های زمان–فرکانس پیشنهاد شده‌است. برای این منظور، نمایش Choi-Williams برای به دست آوردن الگوی دو بعدی فضایی سیگنال دریافتی استفاده می شود. پس از آن، یک مدل عمیق برای حذف نویز از سیگنال استخراج ویژگی‌های قوی و متمایز از الگوی فرکانس زمانی، بر اساس خودرمزگزار و شبکه‌های عصبی کانولوشنی (CNN) ساخته می‌شود. به منظور کاهش تأثیر نویز و اختلالات متخاصم، یک پایگاه داده جدید از الگوهای مدولاسیون مختلف با نویزهای مختلف AWGN و کانال ریلی محوشونده ایجاد شده است که به مدل کمک می کند تا از اثرات نویز بر تشخیص مدولاسیون جلوگیری کند. پایگاه داده ما شامل مدولاسیون های راداری مانند کدBarker ، LFM، Costas و Frank است که به عنوان مدولاسیون های پرکاربرد در ارتباطات بی سیم شناخته می شوند. درواقع، نوآوری روش پیشنهادی، اولا ایجاد این پایگاه‌داده جدید و ثانیا طراحی مدل آگاه به نویز است. نتایج تجربی نشان می‌دهد که مدل پیشنهادی عملکرد برتر را برای تشخیص طبقه‌بندی خودکار با ۹۹.۲٤ درصد دقت در محیط نویزی با حداقل SNR 5-dB به دست می‌آورد در حالی که دقت در SNR 5-dB و f=15 هرتز فرکانس داپلر ۹۷.۹۰ درصد است. روش پیشنهادی باعث پیشرفت دقت به اندازه 5/54% در SNR های منفی و 0/4% ئر SNR های مثبت شده است.