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Multi-scale Deep Learning-based Specific Emitter Identification with Dynamic IoT Environments

Publisher: IEEE

Sayantika Mandal ; Udit Satija ; Jimson Mathew ; Hugeng Hugeng ; Choo W. R. Chiong All Authors

Abstract:
Specific Emitter Identification (SEI) is critical for the precise determination of the source in different applications including, Autonomous Aerial Vehicle (AAV) networks, and Internet of Things (IoT) networks where heterogeneous legitimate and malicious emitters connect and leave the network frequently. Current SEI algorithms extract Radio Frequency (RF) fingerprints from the hardware impairments of the emitters under the simple wireless channels and fixed number of modulation schemes. However, these RF fingerprints are severely impacted by heterogeneous emitters with diverse modulations and different combinations of wireless channels. Therefore, in this paper, we propose a novel multiscale deep-learning (MSDL)-based method to study the performance of SEI under dynamic environments. The proposed method explores the multi-scale view of received radio signals using a recently proposed Fixed Boundary Range-based Empirical Wavelet Transform (FBREWT). The decomposed modes are then combined with a deep Convolutional Neural Network (CNN) for SEI under diverse modulations and different combinations of channel conditions, including Additive White Gaussian Noise (AWGN), Rayleigh Fading (RaFa) coupled with AWGN and Rician flat fading (RiFa) coupled with AWGN with both single-hop (SH) and relaying (RH) communication scenarios. Experimental results demonstrate the superiority of the proposed method for SEI over other existing techniques in both SH and RH scenarios.

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Multi-scale Deep Learning-based Specific Emitter Identification with Dynamic IoT Environments

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***Abstract*—Specific Emitter Identification (SEI) is critical for the precise determination of the source in different applications including, Autonomous Aerial Vehicle (AAV) networks, and Internet of Things (IoT) networks where heterogeneous legitimate and malicious emitters connect and leave the network frequently. Current SEI algorithms extract Radio Frequency (RF) fingerprints from the hardware impairments of the emitters under the simple wireless channels and fixed number of modulation schemes. However, these RF fingerprints are severely impacted by heterogeneous emitters with diverse modulations and different combinations of wireless channels. Therefore, in this paper, we propose a novel multiscale deep-learning (MSDL)-based method to study the performance of SEI under dynamic environments. The proposed method explores the multi-scale view of received radio signals using a recently proposed Fixed Boundary Range-based Empirical Wavelet Transform (FBREWT). The decomposed modes are then combined with a deep Convolutional Neural Network (CNN) for SEI under diverse modulations and different combinations of channel conditions, including Additive White Gaussian Noise (AWGN), Rayleigh Fading (RaFa) coupled with AWGN and Rician flat fading (RiFa) coupled with AWGN with both single-hop (SH) and relaying (RH) communication scenarios. Experimental results demonstrate the superiority of the proposed method for SEI over other existing techniques in both SH and RH scenarios.**

***Index Terms*—Deep CNN, empirical wavelet transform, radio frequency fingerprints, specific emitter identification.**

I. Introduction

The proliferation of the Internet of Things (IoT) involves the surge in internet-connected semi-autonomous devices comprising cheap sensing, computing, networking, and actuation abilities. The use of IoT devices is progressing exponentially and is projected to reach approximately 75 billion by 2025 [1]. However, 70 % of these IoT devices currently operate without encryption safeguards. This alarming trend can be attributed to several factors: 1) limited computational capabilities, 2) the cost increment associated with implementing encryption, and 3) the scalability issues due to encryption implementation and management [1]. Consequently, these inadequately secured IoT devices and associated infrastructure are vulnerable to potential attacks. Hence, there exists an urgent demand for an IoT security strategy capable of thwarting attacks where deceptive devices impersonate authorized IoT devices to evade digital authentication mechanisms. This demand is further amplified because malicious actors exploit this vulnerability not only to target IoT devices but also to compromise the entire IoT infrastructure [2].

Recently, a promising solution called SEI at the physical layer has emerged as a viable means to address this critical security need within the IoT ecosystem [3]. SEI techniques extract external characteristics or features from a received signal, that reveal the emitter's specific and non-intentional characteristics that can be used to identify individual radio emitters [3]. These external characteristics, known as RF fingerprints, are predominantly caused by distinctive hardware imperfections in transmitters, which are unrelated to the content of information [4]. RF fingerprinting plays a growing role in military [5] and civil domains [6], especially in traffic analysis in battlefield spectrum management [7], high-mobility communication [8], and wireless network security [9], due to its uniqueness and difficulty to counterfeit. SEI has applications in radar systems, as well as in determining interference sources. There are three major steps involved in the emitter identification process: RF fingerprints or feature extraction from the received signal; comparison with a categorized set of features; and matching these features with the appropriate class [10]. Most of the SEI techniques exploit steady-state RF fingerprints using a number of methods, including bi-spectral characteristics [11], bio-inspired algorithms [12], cumulants [13], preambles, and approaches based on time-frequency signal representation [14], which is the most commonly used representation. Different Time-Frequency (TF) signal representations including Short-Time Fourier Transform (STFT) [15], Wigner and Choi-Williams TF distributions [16], Hilbert-Huang Transform (HHT) [17], variational mode decomposition [10], are also exploited for SEI. These methods rely only on a few dimension-reduced features which may be severely impacted by different channel conditions [18].

Recently, deep learning (DL)-based techniques [19], [20], have been explored for SEI which can extract features from the received signals in order to further improve identification performance and outperform traditional approaches [21]. However, in the IoT network, different emitters create a time-varying dynamic environment due to the mobility of the transmitter and receiver and different wireless channel conditions [22]. Further, different emitters use various modulation formats and communicate in a cooperative (using relay) or in a non-cooperative environment [23]. Under these circumstances, deep learning-based SEI techniques result into poor identification performance [21]. Therefore, in this paper, we present a novel MSDL method for SEI that combines the benefits of both multi-scale representations of the signal using wavelet and deep Learning techniques such as CNN. In multi-scale representation, the local information of the original signal is captured by subbands at different scales. It has been demonstrated that deep neural networks formulated with subband signals of different scales are effective for classification tasks [24]. In order to obtain a multi-scale representation of the received signal, we exploit the recently proposed Fixed Boundary Range-based Empirical Wavelet Transform (FBREWT) which substantially reduces the computational complexity by fixing the boundary points to obtain subbands, unlike EWT which applies empirical scaling and wavelet functions to all the detected boundary points [25]. Further, these subbands containing multi-scale representation are fed to deep CNN for extracting RF fingerprints or features specific to an emitter and then identifying the emitters. We refer to our method as the FBREWT-based MSDL method for SEI.

A. *Contributions of the Paper*

- Proposed a MSDL network to extract reliable emitter-specific RF fingerprints.
- The performance of the proposed method is evaluated in an IoT dynamic environment considering the cases of single and multi-hop relaying emitters scenarios and under different time-varying channel conditions including, AWGN, the combination of RaFa and AWGN channels, and lastly, the combination of RiFa, RaFa and AWGN channels, exclusively in the RH scenario.
- The proposed method's comparative performance in identifying specific emitters with the same and different modulation schemes of different emitters is also demonstrated considering the fact that IoT devices can use a large range of modulation schemes.

II. System Model

In this work, we have considered both SH and RH communication scenarios to analyze the SEI under AWGN channel, RaFa and RiFa channel. We considered different emitters with six types of digital modulation schemes including 2 and 4 Phase-Shift Keying (BPSK and QPSK), 64-array Quadrature Amplitude Modulation (64-QAM), Pulse Amplitude Modulation (PAM4), and Gaussian and Continuous Phase Frequency-Shift Keying (GFSK and CPFSK) and three types of analog modulated radio signals belonging to Broadcast Frequency Modulation (B-FM) and Dual Side-Band and Single Side-Band Amplitude Modulation (DSB-AM and SSB-AM) schemes. The general representation of a radio signal, r_t at the receiver section is given as follows [25]:

$$r_t = H_i x_t + n_t, \tag{1}$$

where x_t is the specific emitter's output radio signal at time t, given the signal $s_t = \Re\left\{m_t e^{j2\pi f_c t}\right\}$ as the input. m_t is the base-band modulated signal, f_c is the carrier frequency, n_t is the AWGN added, unknown at the receiver end and H_i refers to the fading coefficient or the Probability Density Function (PDF) for the fading channel between the i^{th} transmitter and receiver with $i = 1, 2, \ldots, E$. Here, E denotes the number of emitters. The AWGN channel has a factor H_i of 1. In addition, we use the PDFs of RaFa [26], and the RiFa [27] channels to evaluate the modulated radio signal at the receiver end.

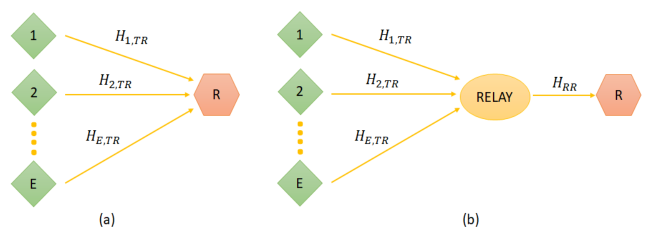

Fig. 1. System model for (a) SH, and (b) RH communication systems.

1) SH Communication Scenario: In the SH scenario, the received signal consists only of the transmitter's RF fingerprints, which are unique to each emitter. A typical SH communication system is shown in Fig. 1(a). In general, the Taylor polynomial model describes the transmitter amplifier's non-linear response [28]. The output of the amplifier at an emitter i is:

$$x_t = \sum_{k=1}^{T_e} \beta_{i,k} \left(s_t\right)^k, \tag{2}$$

where T_e is the order of a specific emitter's Taylor polynomial which we considered as 3 for all emitters and $\beta_i = \left(\beta_{i,1}, \ldots, \beta_{i,T_e}\right)^T$ denotes the Taylor polynomial or non-linearity coefficients, which represents the RF fingerprint of the emitter. These coefficients are considered as $(1, 0.5, 0.3)$, $(1, 0.08, 0.6)$, $(1, 0.01, 0.01)$, and $(1, 0.01, 0.4)$ [10] for emitter 1, 2, 3, 4 respectively. Substituting (2) into (1), the received signal transmitted by an emitter i can be given as:

$$r_t = H_i \sum_{k=1}^{T_e} \beta_k \left(s_t\right)^k + n_t, \quad i = 1, 2, \ldots, E. \tag{3}$$

We generated radio signals under a AWGN channel and a combination of RaFa and AWGN channel with noise added to the modulated signal at various SNR levels [29].

2) RH Communication Scenario: Now, we consider the case of the two-hop relaying scenario shown in Fig. 1(b). The signal is amplified and re-transmitted at the relay before being collected by the receiver. At the relay, the signal is amplified and re-transmitted before it is received by the receiver. The relay's power amplifier's system response z_t can also be expressed as a Taylor polynomial:

$$z_t = \sum_{j=1}^{T_r} \alpha_j \left(y_t\right)^j , \tag{4}$$

where T_r is the Taylor polynomial order which we also considered as 3, α represents the relay's non-linear coefficients which are taken as $(1, 0.1, 0.1)$ [10] for relay in this work and y_t is the received signal at the relay represented by an equation similar to (3):

$$y_t = H_{i,TR} x_t + n_t, \quad i = 1, .., E. \tag{5}$$

Here, we represent the fading channel coefficient between i^{th} emitter and relay by $H_{i,TR}$. The received signal re-transmitted from the relay or the signal received at the receiver is written by combining (2), (4), and (5):

$$\begin{aligned} r_t &= H_{RR} z_t + \eta_t \\ &= H_{RR} \sum_{j=1}^{T_r} \alpha_j \left(H_{i,TR} \sum_{k=1}^{T_e} \beta_{i,k} \left(s_t\right)^k + n_t \right)^j + \eta_t, \end{aligned} \tag{6}$$

where, H_{RR} is the coefficient of the fading channel from the relay to the receiver, and η_t is the AWGN added at the relay. Hence the received signal possesses the mixture of features of emitter and relay, which may degrade the performance of the identification.

In this two-hop RH scenario, noise is added to the modulated radio signals for different SNR values under the following fading channel cases: (1) AWGN channels for both the hops (emitter-relay and relay-receiver); (2) Combination of AWGN and RaFa channels for both the hops; and (3) Combination of AWGN and RiFa channels between the emitter and relay, and combination of AWGN and RaFa channels between the relay and receiver.

III. Proposed Methodology

In this section, we present our FBREWT-based MSDL method for SEI. Figure 2 depicts the block diagram of the proposed methodology. The proposed method consists of two stages: During the first stage, received radio signals with different modulation types are fed to FBREWT to decompose into subbands. Then, in the second stage, all decomposed subbands are fed to deep CNN for feature extraction followed by emitter identification. In this work, we consider three cases in SEI with two emitters ($E = 2$), three emitters ($E = 3$), and four emitters ($E = 4$) subsequently. The major stages of the proposed method are as follows:

A. FBREWT-based Signal Decomposition

In this work, the FBREWT filter-bank-based signal decomposition technique is used for evaluating sub-band signals from each emitter's radio signal. A special case of EWT, FBREWT requires the boundary points to be initialized prior to the non-stationary signal decomposition [24]. A received radio signal's Fourier spectrum is computed in the first step of FBREWT. The Fourier transform of the radio signal, r_t with $t = 0, 1, 2, ..., T-1$ is expressed as [30], [31]:

$$\tilde{r_k} = \sum_{t=0}^{T-1} r_t e^{-j\frac{2\pi nk}{T}}, \tag{7}$$

where 'k' is the Fourier spectrum frequency bin which will lie within the range [0 F_s/2], F_s is the sampling frequency, and $\tilde{r_k}$ is the Fourier coefficient at k_{th} frequency bin. In FBREWT, the filter bank is constructed by splitting the Fourier spectrum of the radio signal into parts based on the fixed boundary points list within the range $[0\pi]$ or the list of frequency points in the range [0 F_s/2] [24]. The p_{th} boundary point (B_p) and p^{th} frequency point (F_p) are mathematically related as [24]:

$$F_p = \frac{B_p F_s}{2\pi}. \tag{8}$$

By utilizing fixed boundary points, for each radio signal, we have generated 16 sub-band signals. In order to segment the frequency spectrum, we have used the following boundaries: [0.12, 0.24, 0.36, 0.48, 0.60, 0.72, 0.84, 0.96, 1.08, 1.20, 1.6, 2.0, 2.3, 2.7, 2.9] [24]. Sub-band signals are then approximated using an inverse discrete Fourier transform of the product of the radio signal spectrum with Mayer and Little-Wood Paley's wavelet-based scaling and wavelet functions in the frequency domain.

B. CNN-based Feature Extraction for SEI

In this work, we utilized a deep 2-dimensional CNN (2D-CNN) model with the architecture as depicted in Fig. 2, for SEI with the 16 sub-band signals that are generated with FBREWT. The input to the 2D-CNN is a 2D matrix of size 16×1024 as there are 16 sub-band signals of one radio signal frame consisting of 1024 samples. The CNN model consists of five 2D-convolution layers that extract features from the input sub-band signals matrix, six batch normalization layers to normalize the data at different stages in the network for speeding up training, and five Max-pooling layers to reduce the extracted training features. Each convolution layer applies zero padding to the input and consists of 2^{i+2} number of filters, where $i = 1, 2, ..., 5$, represents the 5 convolution layers in the 5 2D-convolutional blocks as shown in Fig. 2 (b), with a rectangular filter size of 5×9. These layers apply the non-linear $tanh$ activation function to the learned feature maps. The activated feature maps are batch-normalized and then down-scaled by the $Maxpooling$ layers with a rectangular filter size of 2×4 and a stride of 2×2. The CNN layers are followed by a dense fully-connected layer, a $softmax$ activation layer and the final output cross-entropy layer which calculates the categorical cross-entropy loss for performing

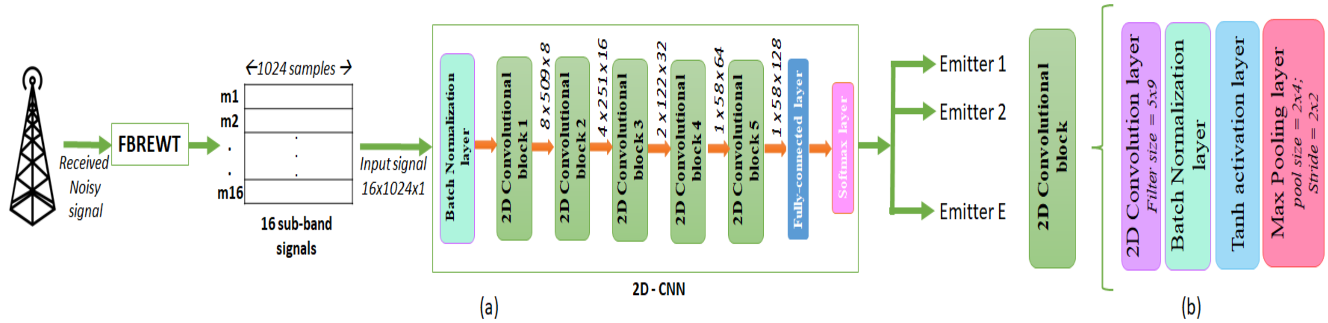

Fig. 2. Block diagram depicting the proposed FBREWT domain MSDL method for SEI using CNN.

multi-class classification. This loss is back-propagated and then minimized over the training process using an optimizer algorithm. The output dense layer size is the number of emitters (E) to be identified in the SEI problem.

IV. Experiments

A. Training Data Generation

In both communication scenarios, radio signals for emitters are generated by creating a random data signal and modulating it with nine modulation schemes. This produces 4500 signals, spanning -10dB to 30dB in 10dB increments, with 500 for each of the nine modulation types. The modulated signals are represented as Taylor polynomials of order 3 with preset coefficients. After channel transmission and noise introduction, transients are removed. The signal is then standardized to a 1024-sample size at a 200KHz sampling frequency, following methods in [25] and [32]. These signals are divided into 16 sub-band signals using the FBREWT filter bank, with input dimensions of [16 × 1024] for training a deep CNN model. Training lasts for 35 epochs using mini-batch stochastic gradient decent (SGD) with a batch size of 128 and a variable learning rate to minimize the cost function as per [24] and [25]. An initial learning rate of 0.004 is assumed, which drops by a factor of 0.5 after every five epochs. Using hold-out partitioning methodology and a 0.1 partition rate, the total number of radio signals generated for training purposes is divided, where 90% of the signals are used for training and the rest 10% for validation.

B. Testing Experiments

The trained CNN models are evaluated on a separate test dataset to examine how unknown modulation schemes at the receiver affect emitter identification. Our objective is to identify emitters via RF fingerprints without relying on modulation recognition [25]. The test dataset is generated using the same procedure as the training data for subsequent experiments.

1) Experiment 1 (same modulations): : In this case, all emitters are equipped with radio signals modulated with the same scheme, chosen from the nine available. Consequently, each emitter consists of 450 radio signals (10% of the training set), all modulated with the same scheme, resulting in a uniform modulation set.

2) Experiment 2 (different modulations): : Here, each emitter employs a distinct modulation scheme to generate radio signals. For instance, if there are E emitters to classify, each emitter contains 450 radio signals, each modulated with E different modulation schemes, leading to a diverse modulation set for this experiment.

V. Performance Evaluation and Discussion

In this section, we evaluate SEI performance in SH and RH communication scenarios involving 2, 3, and 4 emitters. We analyze the effect of different modulation schemes on identification accuracy using average classification accuracy (P_c) under varying SNR and channel conditions.

A. SEI in Single Hop Scenario

The performance results in terms of P_c (%) at different SNR are depicted in Table I for the case of 2 and 3 emitters and 4 emitters, respectively, under the SH scenario with AWGN and RaFa channel. It can be observed from the table that the P_c increases with the SNR value. At all SNRs, the SEI performance for the modulation set containing the same modulation schemes (experiment 1) outperforms the performance for the modulation set containing different modulations (experiment 2). In the case of 2 emitters, the emitter signals of all modulation sets except those containing DSB-AM and SSB-AM modulations are completely classified with 100% P_c at high SNRs for experiment 1. For positive SNRs, the emitter identification performance is superior for both modulation experiments 1 and 2. However, the performance drops as the number of emitters are increased. It can also be deduced that the emitters with SSB-AM and DSB-AM modulated radio signals are not classified accurately at any SNR, with the P_c not exceeding 88% even at high SNRs for all emitter cases and modulation experiments. This happens due to the indistinguishable nature of these two modulation types. The modulation sets comprising GFSK, CPFSK, and/or B-FM modulations are able to offer superior performance as compared to other modulation sets even at low SNRs and for all the emitter cases. It can be seen from the plots that GFSK modulation achieves a P_c of nearly 84% even at -10 dB SNR for the 2 emitters classification case in experiment 1. At high SNRs, the classification is nearly 100% for these modulation sets.

Further, under the combination of Rayleigh fading and AWGN channels, the P_c values indicate that the SEI performance for experiment 1 outperforms that for experiment 2. In experiment 1, for 2 emitters case, the P_c for emitters with BPSK modulated signals drops drastically for all SNRs,

TABLE I

Probability of correct classification in % for SH scenario

		Single Hop-AWGN Channel					Single Hop-Rayleigh Channel				
Emitters	Modulation Type	SNR(dB)					SNR(dB)				
		-10	0	10	20	30	-10	0	10	20	30
2	BPSK, BPSK	49.89	74.22	99.33	100	100	49.44	50.44	50.00	49.89	55.00
	QPSK, QPSK	48.11	32.78	72.22	97.56	100	48.11	50.44	53.44	85.67	99.33
	64QAM, 64QAM	46.78	47.44	84.89	99.22	100	49.44	50.44	57.44	92.11	97.89
	PAM4, PAM4	50.67	65.56	97.78	99.89	100	49.67	56.89	88.33	99.89	100
	GFSK, GFSK	83.89	100	100	100	100	50.22	96.78	100	100	100
	CPFSK, CPFSK	61.89	99.44	100	100	100	50.67	99.67	100	100	100
	B-FM, B-FM	54.44	94.78	99.78	99.44	99.89	52.11	91.33	99.67	99.11	99.44
	DSB-AM, DSB-AM	51.89	51.22	55.89	70.56	83.22	50.22	47.78	64.67	77.78	84.11
	SSB-AM, SSB-AM	50.78	51.78	59.89	80.00	80.89	51.33	51.78	69.11	84.56	83.44
	BPSK, QPSK	49.44	52.33	77.67	97.33	100	49.78	51.78	8.33	24.00	97.67
	64QAM, PAM4	48.67	61.00	94.33	99.89	100	49.56	44.89	73.67	81.44	80.67
	QPSK, DSB-AM	67.67	55.11	79.33	93.00	88.78	48.00	66.22	76.22	84.89	90.22
	GFSK, CPFSK	64.11	99.89	100	100	100	47.78	97.11	100	100	100
	B-FM, DSB-AM	53.33	74.33	86.22	93.44	93.22	49.67	66.44	79.56	86.00	92.22
	B-FM, 6QAM	47.33	74.11	92.56	99.22	99.44	48.11	71.44	92.67	96.89	99.78
	DSB-AM, SSB-AM	53.22	49.33	62.22	74.44	81.78	51.00	51.67	71.22	77.56	81.22
	QPSK, 64QAM	48.89	48.44	82.00	98.89	99.89	51.11	54.67	53.67	98.89	100
	BPSK, CPFSK	63.56	97.56	100	100	100	48.67	92.11	95.56	100	100
3	BPSK, BPSK, BPSK	38.00	58.07	75.93	92.30	98.96	32.81	31.48	30.67	33.33	23.33
	QPSK, QPSK, QPSK	31.26	23.93	50.59	77.48	97.33	32.74	32.67	31.56	18.81	29.56
	64QAM, 64QAM, 64QAM	28.67	25.85	61.04	79.04	91.93	31.78	34.67	31.11	33.33	32.59
	PAM4, PAM4, PAM4	32.67	37.11	67.85	85.11	96.89	34.96	32.52	33.11	44.00	30.89
	GFSK, GFSK, GFSK	61.04	99.26	100	100	100	33.48	64.37	66.67	66.67	66.67
	CPFSK, CPFSK, CPFSK	46.00	97.11	100	100	100	28.89	60.37	38.00	34.52	33.33
	B-FM, B-FM, B-FM	34.74	79.11	96.37	97.48	92.44	32.74	41.63	50.74	48.89	30.44
	DSB-AM, DSB-AM, DSB-AM	33.04	32.89	39.56	47.93	65.33	33.56	33.11	29.04	31.19	33.33
	SSB-AM, SSB-AM, SSB-AM	33.63	33.26	40.96	55.33	68.44	33.04	34.00	29.56	35.63	33.33
	BPSK, QPSK, 64QAM	47.33	62.59	72.30	83.19	94.00	44.74	20.96	20.96	26.52	52.15
	64QAM, PAM4, QPSK	34.07	36.96	63.85	81.78	95.78	35.33	35.26	57.63	37.48	33.33
	QPSK, PAM4, DSB-AM	29.85	32.74	55.48	73.41	97.19	34.37	31.78	32.07	87.11	33.33
	B-FM, GFSK, CPFSK	42.07	34.59	51.63	71.63	85.63	37.41	37.33	54.96	67.93	33.33
	B-FM, DSB-AM, SSB-AM	42.15	97.19	99.56	99.93	99.93	22.96	96.22	99.85	69.19	66.52
	GFSK, B-FM, 64QAM	35.33	55.41	56.52	67.33	82.89	33.26	54.96	58.22	62.67	33.41
	CPFSK, SSB-AM, PAM4	51.70	72.07	78.96	83.33	90.59	18.96	60.30	72.37	68.00	58.30
	QPSK, 64QAM, B-FM	41.48	45.04	76.22	94.07	91.63	37.48	43.56	78.22	34.96	49.19
	GFSK, BPSK, CPFSK	41.93	75.63	81.19	94.00	98.96	28.89	52.37	73.56	63.48	67.70
4	BPSK, BPSK, BPSK, BPSK	31.61	46.78	76.78	87.72	99.61	24.17	25.94	32.33	15.94	25.00
	QPSK, QPSK, QPSK, QPSK	22.06	19.56	53.11	77.67	97.39	25.00	27.50	25.06	41.83	25.00
	64QAM, 64QAM, 64QAM, 64QAM	19.67	19.83	55.39	78.33	94.33	24.33	20.78	38.00	40.06	25.06
	PAM4, PAM4, PAM4, PAM4	27.28	39.89	30.11	80.72	97.17	24.56	32.61	50.06	25.33	26.28
	GFSK, GFSK, GFSK, GFSK	60.44	99.44	100	100	100	24.39	98.28	89.17	75.00	27.78
	CPFSK, CPFSK, CPFSK, CPFSK	36.28	98.11	100	100	100	23.44	70.44	92.72	44.22	72.83
	B-FM, B-FM, B-FM, B-FM	26.61	82.94	97.28	94.17	97.67	25.22	35.28	31.56	78.50	50.72
	DSB-AM, DSB-AM, DSB-AM, DSB-AM	26.61	25.56	29.67	35.17	47.44	25.50	24.78	24.06	21.28	38.00
	SSB-AM, SSB-AM, SSB-AM, SSB-AM	26.17	26.17	33.44	37.83	51.83	25.61	24.17	22.89	23.72	47.50
	BPSK, QPSK, 64QAM, PAM4	26.28	32.44	61.33	79.39	95.83	24.56	25.50	12.11	19.22	26.39
	64QAM, PAM4, GFSK, CPFSK	31.78	66.28	88.94	95.89	99.22	22.28	42.28	50.28	24.22	50.00
	QPSK, PAM4, DSB-AM, CPFSK	34.33	44.67	62.89	72.72	85.83	21.22	46.78	57.44	3.89	36.83
	B-FM, GFSK, CPFSK, QPSK	38.94	80.72	95.11	94.06	99.44	20.33	80.22	73.94	75.00	50.72
	B-FM, DSB-AM, SSB-AM, GFSK	29.61	57.56	59.50	59.89	74.17	40.50	53.78	57.33	53.28	11.17
	GFSK, B-FM, BPSK, QPSK	39.33	59.17	84.50	90.28	98.94	14.83	43.67	69.67	43.50	34.11
	B-FM, CPFSK, SSB-AM, PAM4	27.17	55.67	70.78	72.94	85.44	24.56	26.50	57.78	64.44	20.67
	QPSK, 64QAM, B-FM, SSB-AM	31.61	36.72	58.67	80.83	82.94	26.33	26.50	10.83	23.56	51.50
	GFSK, BPSK, CPFSK, PAM4	29.61	61.72	83.78	92.61	99.67	24.78	18.11	25.11	2.17	71.78

TABLE II

Probability of correct classification in % for RH scenario

		AWGN				RaFa+AWGN				RiFa+RaFa+AWGN			
Emitters	Modulation Type	SNR(dB)				SNR(dB)				SNR(dB)			
		0	10	20	30	0	10	20	30	0	10	20	30
2	BPSK, BPSK	64.22	98.56	100	100	50.11	49.78	50.00	50.00	51.11	50.56	50.00	50.00
	QPSK, QPSK	39.11	53.56	93.67	99.89	52.00	50.22	50.00	50.00	50.67	46.78	68.89	50.00
	64QAM, 64QAM	47.22	73.22	97.89	99.89	51.22	59.89	50.00	50.00	49.56	44.56	51.22	50.00
	PAM4, PAM4	59.44	92.11	100	100	62.89	50.00	50.00	50.00	49.89	46.33	50.11	50.00
	GFSK, GFSK	99.44	100	100	100	94.00	100	50.00	100	53.89	73.33	80.00	50.00
	CPFSK, CPFSK	96.78	100	100	100	62.44	95.44	50.00	50.00	50.00	49.89	58.22	50.00
	B-FM, B-FM	86.67	99.11	99.11	99.78	48.78	50.56	53.22	56.44	52.67	48.67	61.78	78.67
	DSB-AM, DSB-AM	49.44	50.67	67.56	81.22	52.00	48.78	49.44	53.44	52.11	49.44	49.33	48.22
	SSB-AM, SSB-AM	48.56	63.11	75.44	78.22	51.89	50.11	48.33	77.56	51.00	50.11	50.33	44.22
	BPSK, QPSK	51.78	71.89	95.56	99.89	50.78	49.56	50.00	50.00	51.44	52.67	50.11	50.00
	64QAM, PAM4	50.33	86.22	99.22	100	49.22	51.00	50.00	50.00	49.44	40.89	46.11	50.11
	QPSK, DSB-AM	56.89	66.33	94.11	96.00	62.00	15.00	61.11	42.22	74.11	70.22	5.78	95.56
	GFSK, CPFSK	97.33	100	100	100	97.11	57.44	50.00	100	51.89	51.89	86.78	50.00
	B-FM, DSB-AM	70.67	83.89	94.22	97.44	53.67	68.89	67.78	51.89	51.89	69.11	60.33	91.00
	B-FM, 6QAM	69.56	87.56	97.56	99.67	49.22	96.22	49.89	59.33	53.44	57.22	45.00	48.89
	DSB-AM, SSB-AM	49.67	48.00	66.56	85.11	50.33	47.00	42.11	48.11	51.22	49.67	52.89	43.00
	QPSK, 64QAM	52.11	67.11	96.78	99.89	50.89	50.89	49.89	50.00	50.78	48.00	50.00	50.00
	BPSK, CPFSK	96.22	99.22	100	100	51.33	51.78	36.78	63.33	45.00	46.56	50.00	59.56
3	BPSK, BPSK, BPSK	50.89	74.67	88.89	98.22	30.15	32.44	33.85	66.00	35.63	41.56	17.26	47.93
	QPSK, QPSK, QPSK	25.48	41.93	74.67	92.22	31.56	30.30	33.63	33.33	32.74	35.11	33.33	33.33
	64QAM, 64QAM, 64QAM	25.19	51.56	75.93	89.78	24.52	21.70	31.48	33.33	31.56	31.56	33.48	33.33
	PAM4, PAM4, PAM4	39.11	64.15	85.26	95.04	29.26	29.26	33.33	7.63	31.70	31.19	35.56	33.33
	GFSK, GFSK, GFSK	94.22	100	100	100	34.30	43.26	11.48	0.00	34.81	39.41	33.41	70.22
	CPFSK, CPFSK, CPFSK	85.63	99.93	100	100	33.78	31.41	68.22	31.26	35.78	35.26	99.85	99.85
	B-FM, B-FM, B-FM	63.78	95.33	93.93	93.48	35.78	32.52	77.78	61.41	34.00	33.70	91.48	82.59
	DSB-AM, DSB-AM, DSB-AM	31.11	37.41	49.04	55.19	33.63	31.11	41.56	28.30	32.37	33.78	37.19	30.52
	SSB-AM, SSB-AM, SSB-AM	33.26	39.26	52.67	61.93	33.41	32.74	34.37	36.67	31.19	34.00	32.67	57.19
	BPSK, QPSK, 64QAM	34.67	36.52	58.22	79.48	91.70	32.96	32.44	32.52	35.19	37.33	30.52	29.41
	64QAM, PAM4, QPSK	29.70	60.44	79.70	96.00	31.26	26.52	66.67	33.33	31.11	35.63	46.59	33.33
	QPSK, PAM4, DSB-AM	34.22	56.89	84.96	88.22	35.93	26.89	39.93	25.63	42.67	32.81	62.07	63.19
	B-FM, GFSK, CPFSK	85.11	99.63	100	99.70	55.56	30.74	59.33	47.63	31.41	34.89	31.04	66.22
	B-FM, DSB-AM, SSB-AM	52.44	60.81	68.07	80.52	31.70	52.07	23.41	54.59	35.93	46.30	36.81	38.07
	GFSK, B-FM, 64QAM	64.37	79.70	86.59	93.70	32.59	25.56	78.59	56.89	37.85	24.37	52.81	35.93
	CPFSK, SSB-AM, PAM4	56.81	61.11	68.37	87.56	36.89	22.81	50.67	9.78	45.93	33.11	38.07	35.48
	QPSK, 64QAM, B-FM	38.96	61.11	85.70	91.41	32.89	51.04	61.41	39.85	25.48	60.37	33.19	86.15
	GFSK, BPSK, CPFSK	64.07	84.44	95.41	98.44	36.22	66.96	34.81	85.63	34.52	41.11	66.67	94.59
4	BPSK, BPSK, BPSK, BPSK	38.89	70.61	85.33	97.89	24.89	20.56	48.28	25.00	28.17	19.94	26.11	25.00
	QPSK, QPSK, QPSK, QPSK	18.00	40.72	74.33	92.83	21.56	23.83	25.17	25.00	27.39	24.22	25.00	25.00
	64QAM, 64QAM, 64QAM, 64QAM	17.11	43.83	72.11	90.50	22.33	24.39	19.00	35.11	26.89	25.22	26.17	25.83
	PAM4, PAM4, PAM4, PAM4	29.06	40.94	53.22	94.00	24.78	26.11	26.11	25.00	26.44	27.11	23.06	25.00
	GFSK, GFSK, GFSK, GFSK	91.83	100	100	100	25.78	75.28	75.00	27.17	24.67	50.33	44.22	35.06
	CPFSK, CPFSK, CPFSK, CPFSK	88.61	100	100	100	25.28	82.06	43.83	25.00	24.33	62.11	100	59.06
	B-FM, B-FM, B-FM, B-FM	68.11	96.72	95.39	96.94	25.00	33.00	76.83	62.67	25.39	37.17	93.83	79.67
	DSB-AM, DSB-AM, DSB-AM, DSB-AM	25.56	27.89	34.50	42.22	24.33	20.89	22.22	45.33	24.50	25.44	26.33	30.83
	SSB-AM, SSB-AM, SSB-AM, SSB-AM	25.61	31.78	36.56	44.28	25.06	20.78	27.83	44.56	24.50	24.28	20.22	27.17
	BPSK, QPSK, 64QAM, PAM4	28.72	54.83	70.89	91.89	25.72	27.11	50.00	25.00	27.56	23.56	24.61	25.00
	64QAM, PAM4, GFSK, CPFSK	59.89	92.00	98.39	98.78	17.39	19.06	25.00	49.94	29.11	51.50	25.00	29.56
	QPSK, PAM4, DSB-AM, CPFSK	44.11	68.44	78.33	82.94	23.33	6.11	26.11	7.00	35.44	24.83	33.72	28.83
	B-FM, GFSK, CPFSK, QPSK	66.06	90.78	98.44	99.22	27.83	17.44	24.22	28.67	23.44	30.39	36.89	56.94
	B-FM, DSB-AM, SSB-AM, GFSK	58.56	62.33	61.89	68.11	24.61	49.78	65.56	15.89	25.94	32.61	29.39	49.28
	GFSK, B-FM, BPSK, QPSK	50.72	68.61	87.50	98.00	35.00	38.72	35.94	30.33	20.22	27.33	43.33	61.00
	B-FM, CPFSK, SSB-AM, PAM4	55.94	74.72	76.78	83.44	28.06	11.50	55.17	32.50	16.17	27.72	60.83	79.11
	QPSK, 64QAM, B-FM, SSB-AM	32.11	52.33	73.00	80.44	21.17	14.89	38.22	60.17	19.89	23.17	37.94	65.11
	GFSK, BPSK, CPFSK, PAM4	49.33	89.50	96.61	98.72	35.67	29.17	50.11	32.06	14.94	28.17	50.11	58.11

and for all other SEI cases, the performance exceedingly degrades for even QPSK, 64QAM, and PAM4 modulations as compared to the AWGN channel. DSB-AM and SSB-AM modulations once again continue to offer degraded emitter identification performance for all cases and experiments with the highest P_c achieved being 84% for the 2 emitters case. Though the modulations GFSK, CPFSK, and B-FM are able to achieve a maximum of 100% for the 2 emitters case, their performance also deteriorates upon increasing the number of emitters, with P_c as low as 30% for even high SNRs. For greater than 2 emitters, the best performance is achieved by the modulation set of all CPFSK modulations in experiment 1 and the modulation set GFSK, BPSK, CPFSK, PAM4 in experiment 2 of 4 emitters case.

B. SEI in Relaying Scenario

The performance results in terms of P_c (%) at different SNRs are depicted in Table II for the case of 2 and 3 emitters under AWGN channel, AWGN+RaFa channel and AWGN+RaFa+RiFa channel. All modulation sets in experiment 1 show high identification probabilities at positive SNRs for all the emitters. The modulations GFSK, and CPFSK achieve 100% classification for all the emitters, whereas for B-FM the classification drops to a little below 100%. However, their performance at low SNRs degrades excessively. The SEI performance is appreciable even in experiment 2 under an increased number of emitters. Like previous scenarios, DSB-AM and SSB-AM modulations provide good performance in only 2 emitter cases with a maximum P_c of 81% attained by DSB-AM in experiment 1.

The performance of emitter identification is degraded in the case of relay between transmitter and receiver with a combination of Rayleigh fading and AWGN channels, as verified from Table II. This degradation occurs due to mixing of RF signature of relay and emitter. Only GFSK or a modulation set containing both GFSK and CPFSK is able to achieve a high classification performance throughout all the cases and modulation experiments. Otherwise, the P_c values are unable to exceed even 70% for all other modulation sets. Furthermore, it can be observed from the table that the SEI performance saturates around a P_c of 50% value for most of the modulation sets where the channel between the emitter and relay is a combination of Rician and AWGN channels and the channel between the relay and receiver is a combination of Rayleigh and AWGN channels. Hence, the emitter identification performance is much reduced as compared to all the abovementioned previous cases. B-FM modulation achieves the best performance in experiment 1 for all the emitters. Further, experiment 2 modulation sets containing B-FM, GFSK, or CPFSK modulations achieved a P_c close to 90% which no modulation set could achieve in experiment 1. Hence, all these findings indicate that the model is unable to achieve systematic results in this scenario due to the effect of the relay and other fading channels. The values of P_c are given in the Table II in percentages for all the emitter identification cases across various SNRs.

VI. Conclusion

This paper proposes an MSDL method using FBREWT for identifying specific emitters from radio signals with nine modulation types. The FBREWT filter bank decomposes received signals, followed by RF fingerprint extraction via deep CNN. Results across modulation and channel combinations in single-hop and relay scenarios show that emitter identification in AWGN channels achieves excellent performance when modulation types are identical.

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